Probabilistic (Logic) Programming and its Applications

Luc De Raedt

with many slides from Angelika Kimmmig

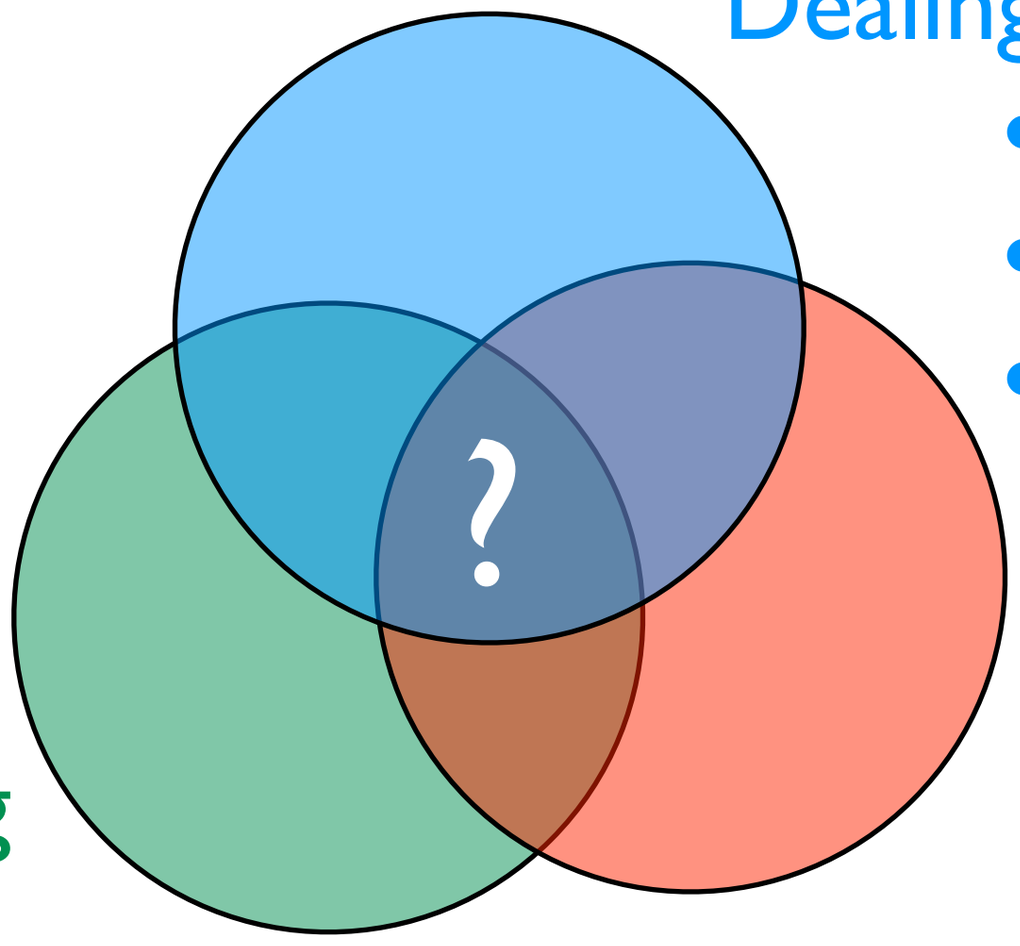
A key question in AI:

Dealing with uncertainty

- probability theory
- graphical models
- ...

Reasoning with relational data

- logic
- databases
- programming
- ...



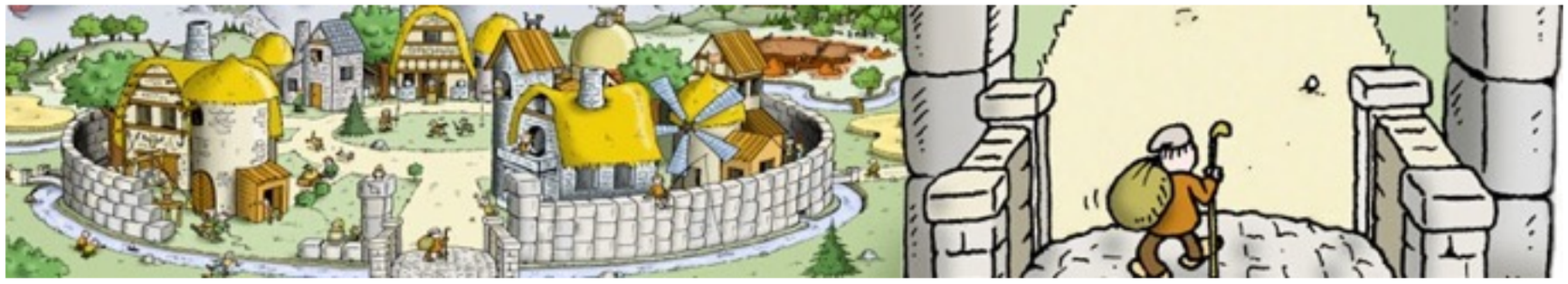
Learning

- parameters
- structure

Statistical relational learning
& Probabilistic Programming

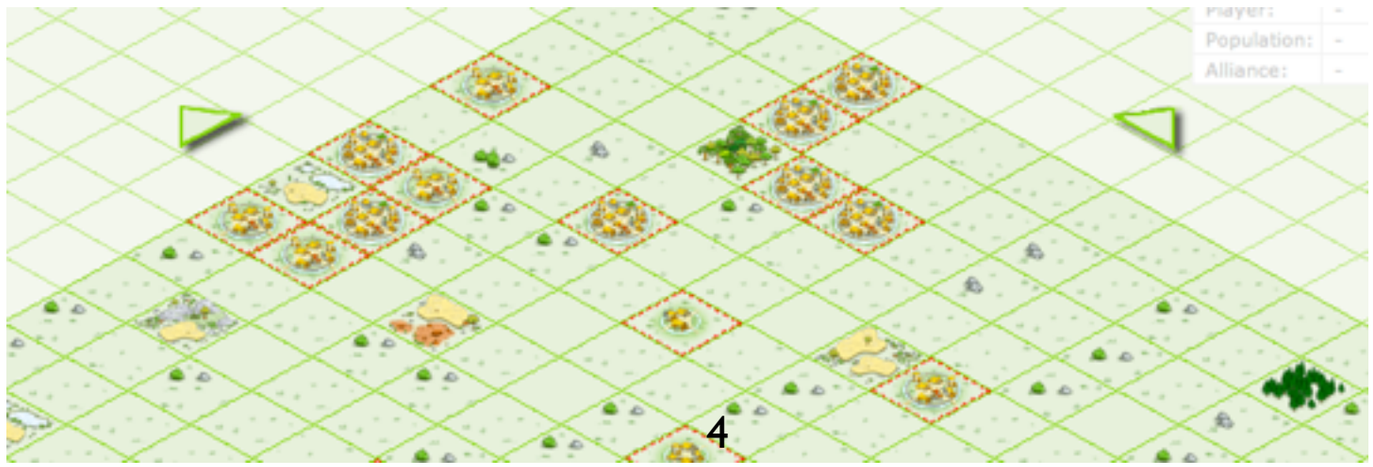
The need for relations

Dynamics: Evolving Networks



- *Travian*: A massively multiplayer real-time strategy game
- Commercial game run by TravianGames GmbH
- ~3.000.000 players spread over different "worlds"
- ~25.000 players in one world

[Thon et al. ECML 08]



World Dynamics

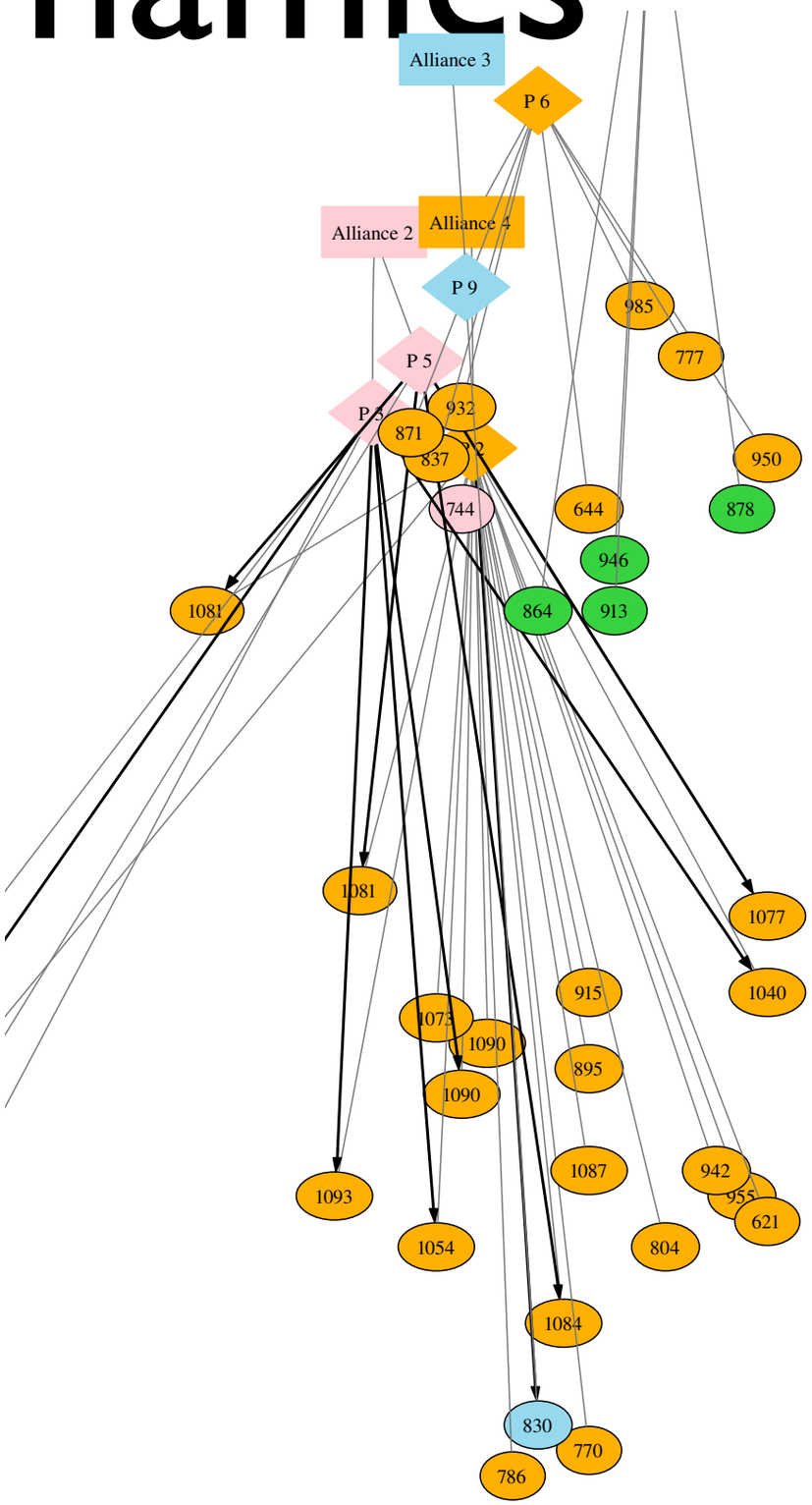
Fragment of world with

~10 alliances
~200 players
~600 cities

alliances color-coded

Can we build a model
of this world ?
Can we use it for playing
better ?

[Thon, Landwehr, De Raedt, ECML08]



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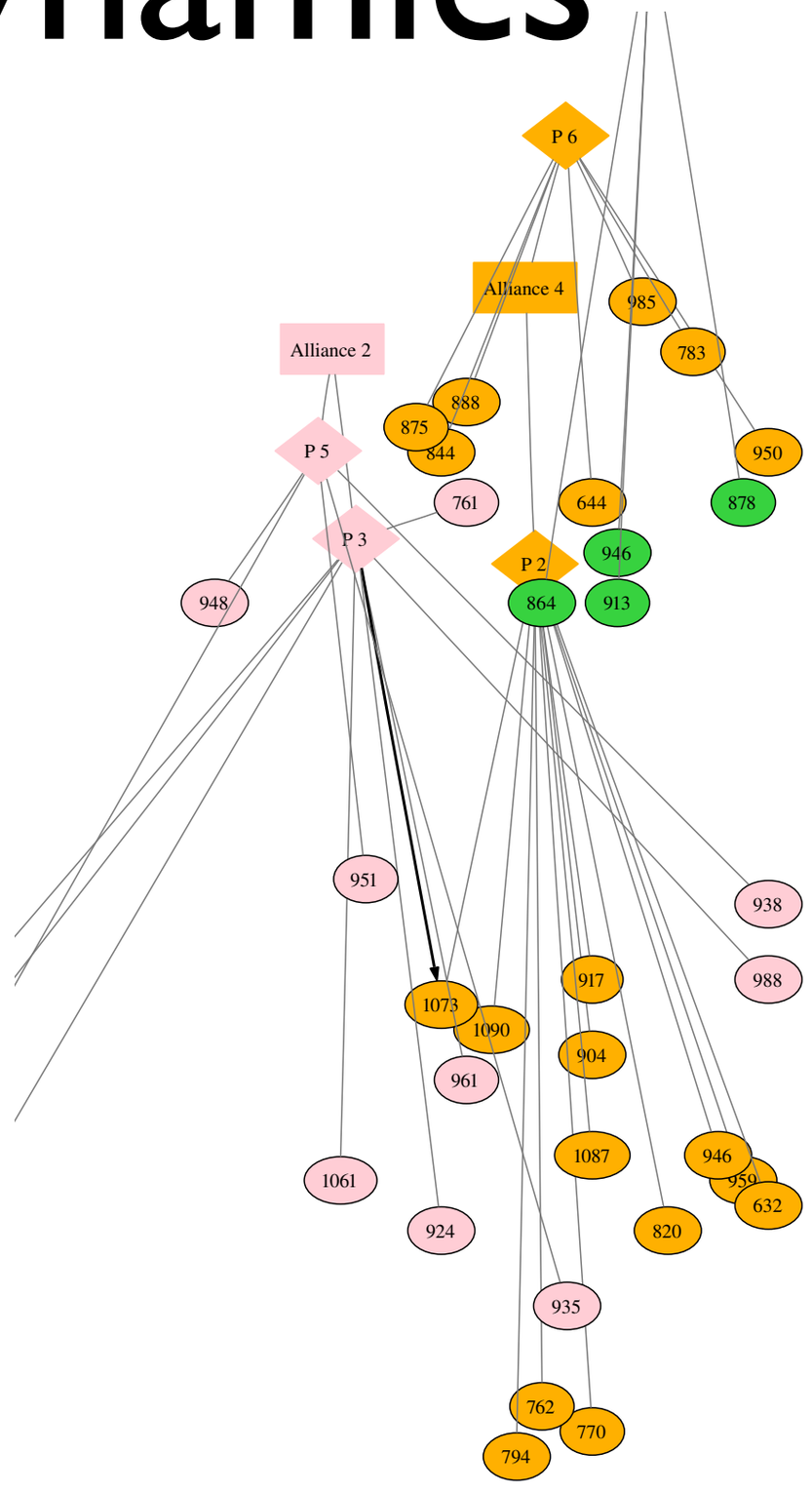

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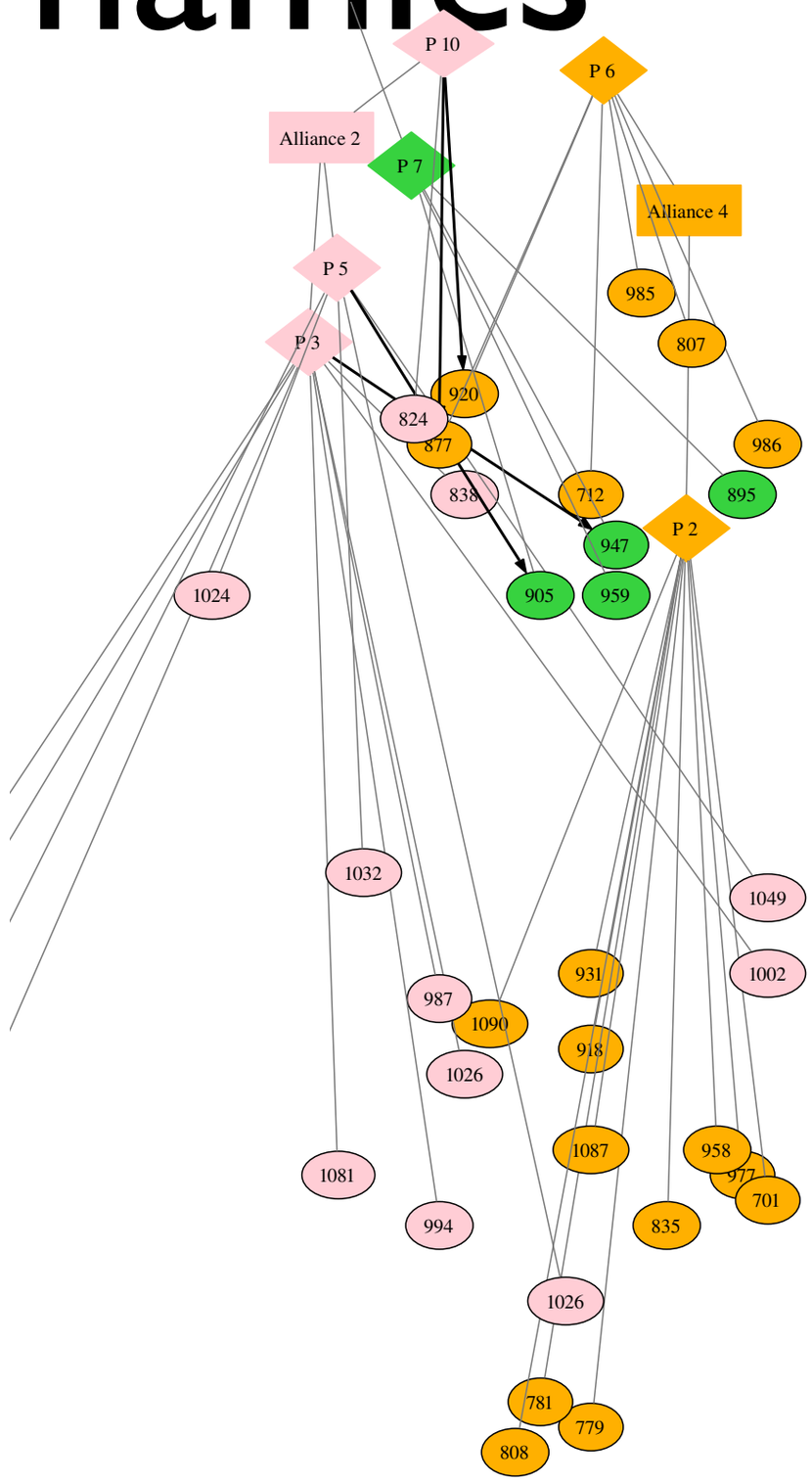
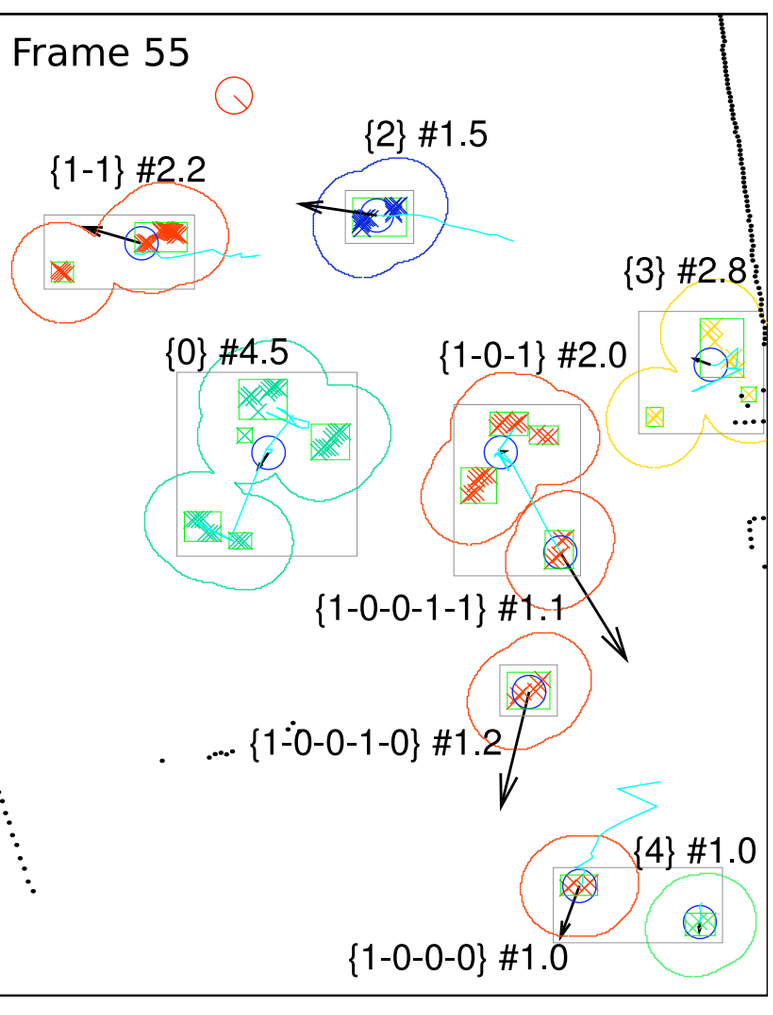


Analyzing Video Data



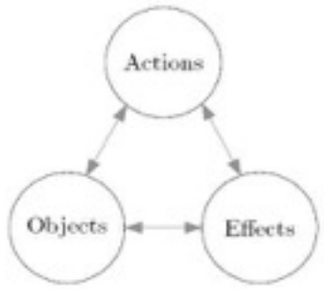
- Track people or objects over time? Even if temporarily hidden?

[Skarlatidis et al, TPLP 14; Nitti et al, IROS 13, ICRA 14]

- Recognize activities?
- Infer object properties?

Learning relational affordances

Learn probabilistic model



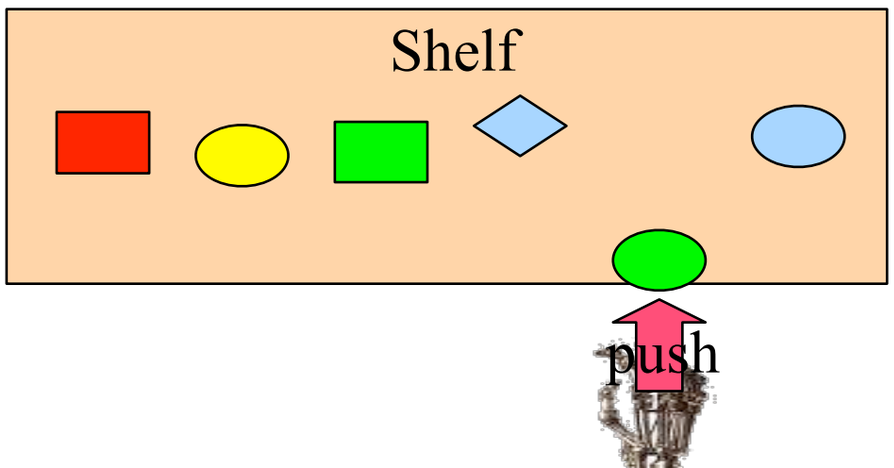
Inputs	Outputs	Function
(O, A)	E	Effect prediction
(O, E)	A	Action recognition/planning
(A, E)	O	Object recognition/selection

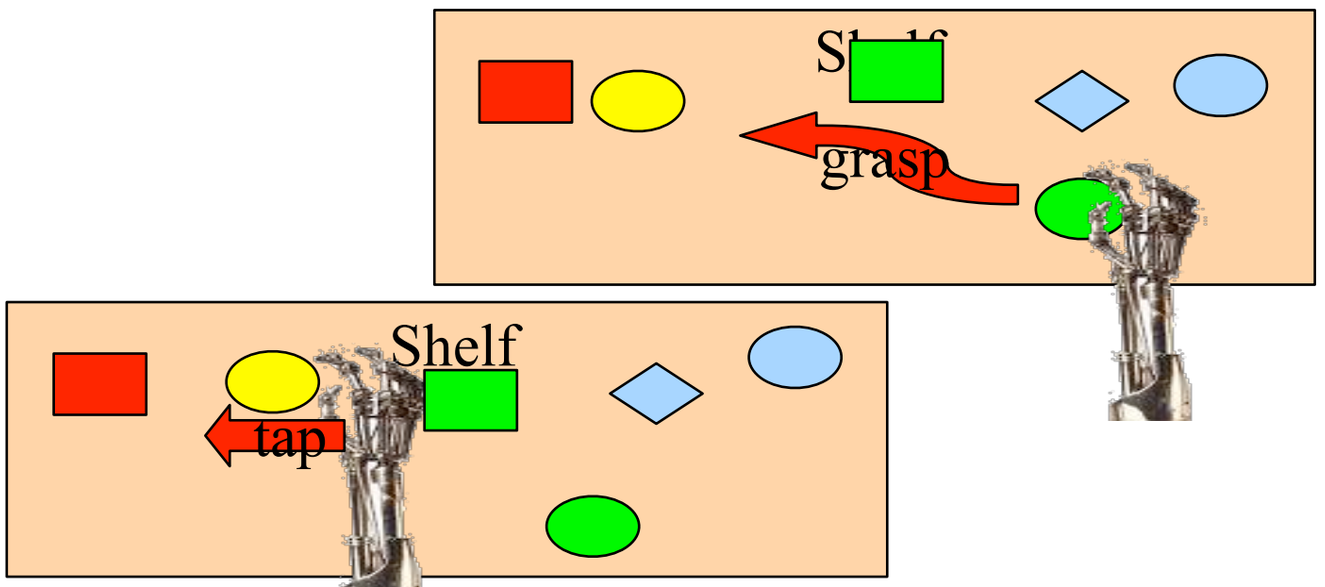
Learning relational affordances between two objects (learnt by experience)

From two object interactions

Generalize to N

***Moldovan** et al. ICRA 12, 13, 14, PhD 15*





Example: Information Extraction

Recently-Learned Facts twitter

Refresh

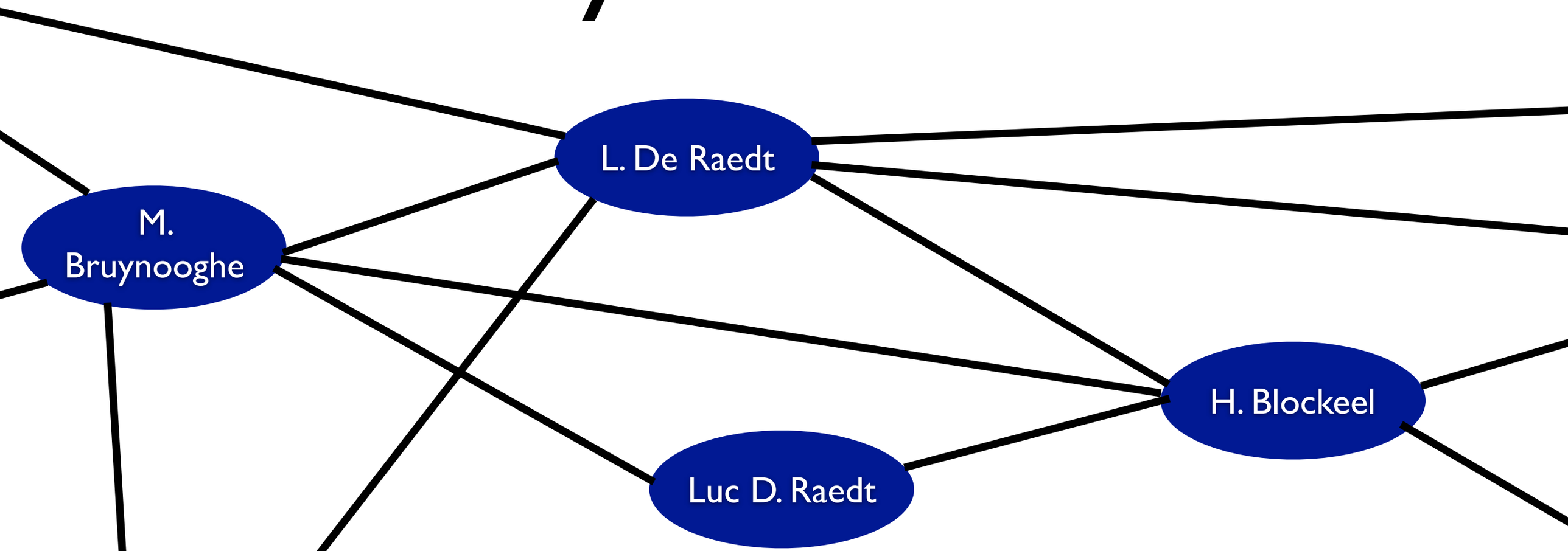
instance	iteration	date learned	confidence
kelly_andrews is a female	826	29-mar-2014	98.7
investment_next_year is an economic sector	829	10-apr-2014	95.3
shibenik is a geopolitical entity that is an organization	829	10-apr-2014	97.2
quality_web_design_work is a character trait	826	29-mar-2014	91.0
mercedes_benz_cls_by_carlsson is an automobile manufacturer	829	10-apr-2014	95.2
social_work is an academic program at the university rutgers_university	827	02-apr-2014	93.8
dante wrote the book the_divine_comedy	826	29-mar-2014	93.8
willie_aames was born in the city los_angeles	831	16-apr-2014	100.0
kitt_peak is a mountain in the state or province arizona	831	16-apr-2014	96.9
greenwich is a park in the city london	831	16-apr-2014	100.0

instances for many different relations

degree of certainty

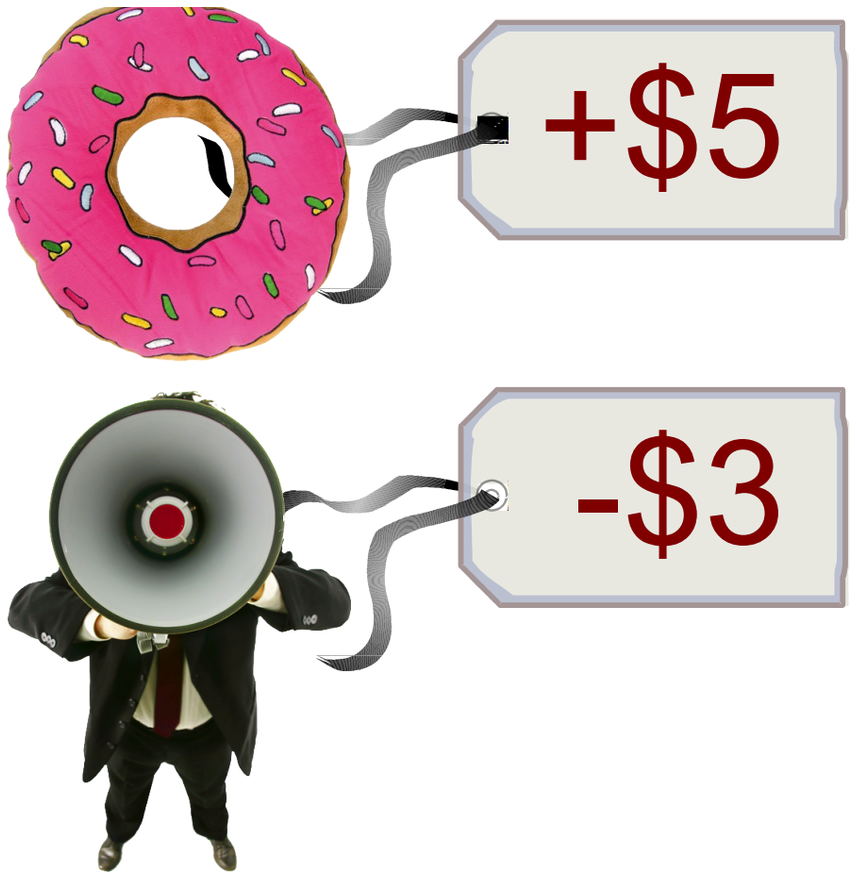
NELL: http://rtw.ml.cmu.edu/rtw/

Entity Resolution

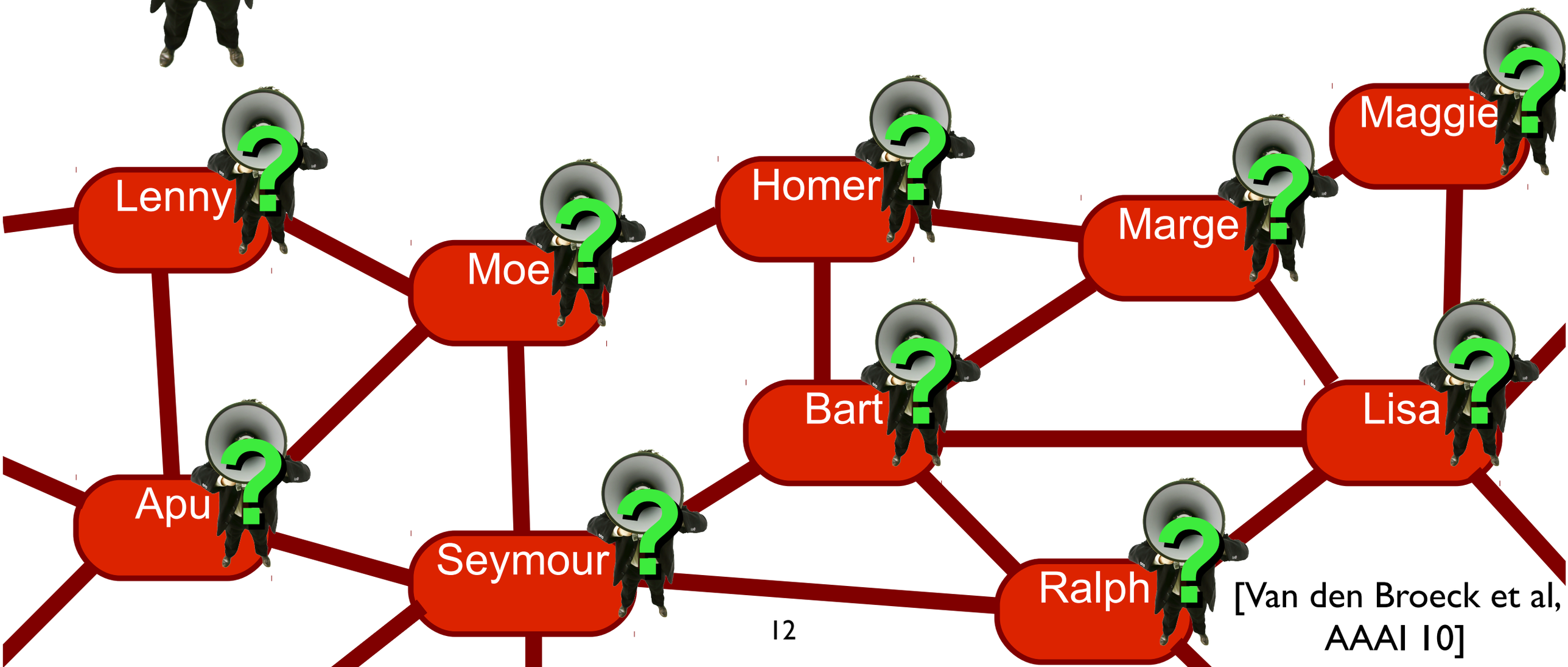


Automatically extracted co-author network: which nodes refer to the same person?

Viral Marketing

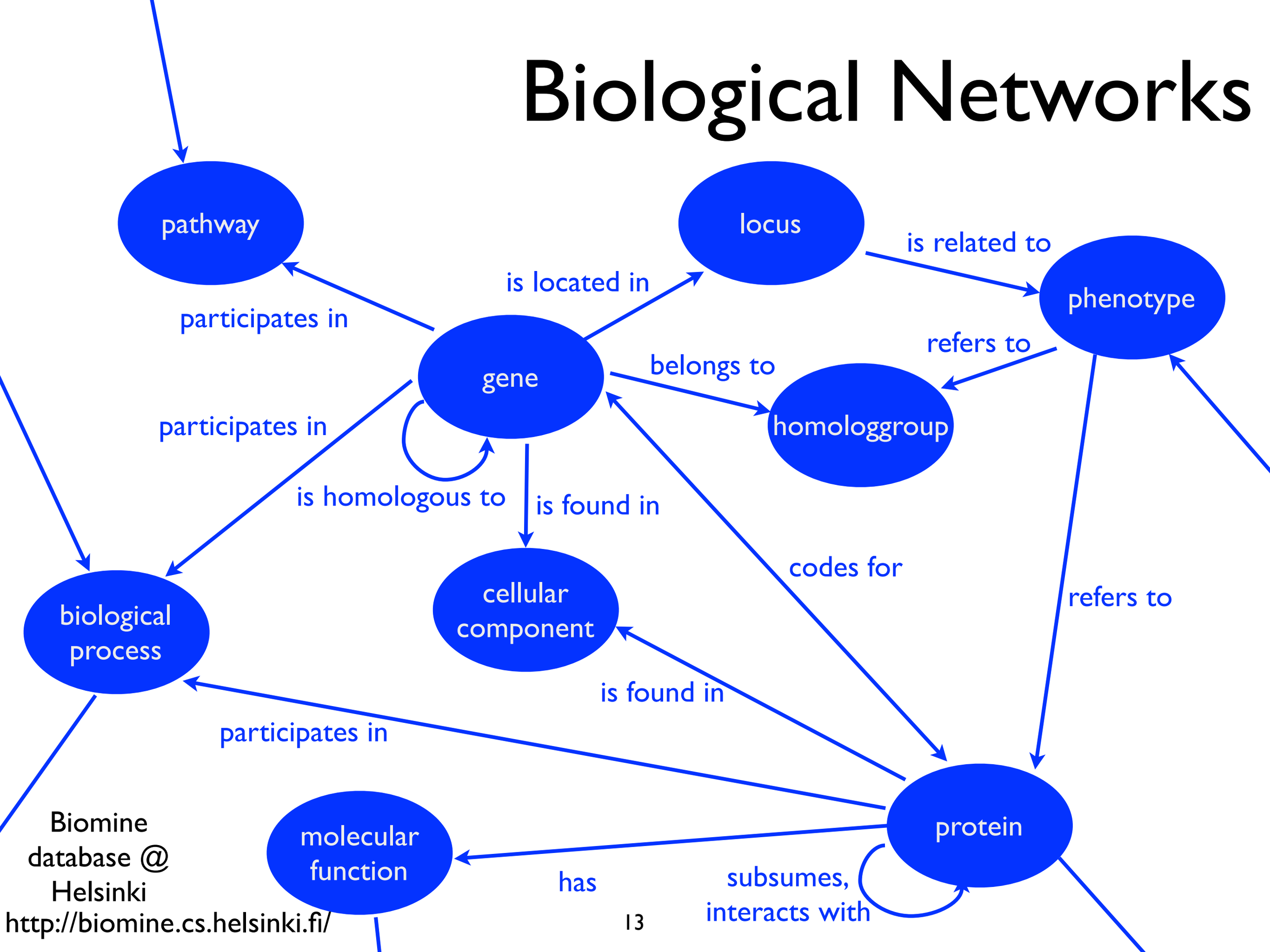


Which advertising strategy maximizes expected profit?



[Van den Broeck et al, AAAI 10]

Biological Networks



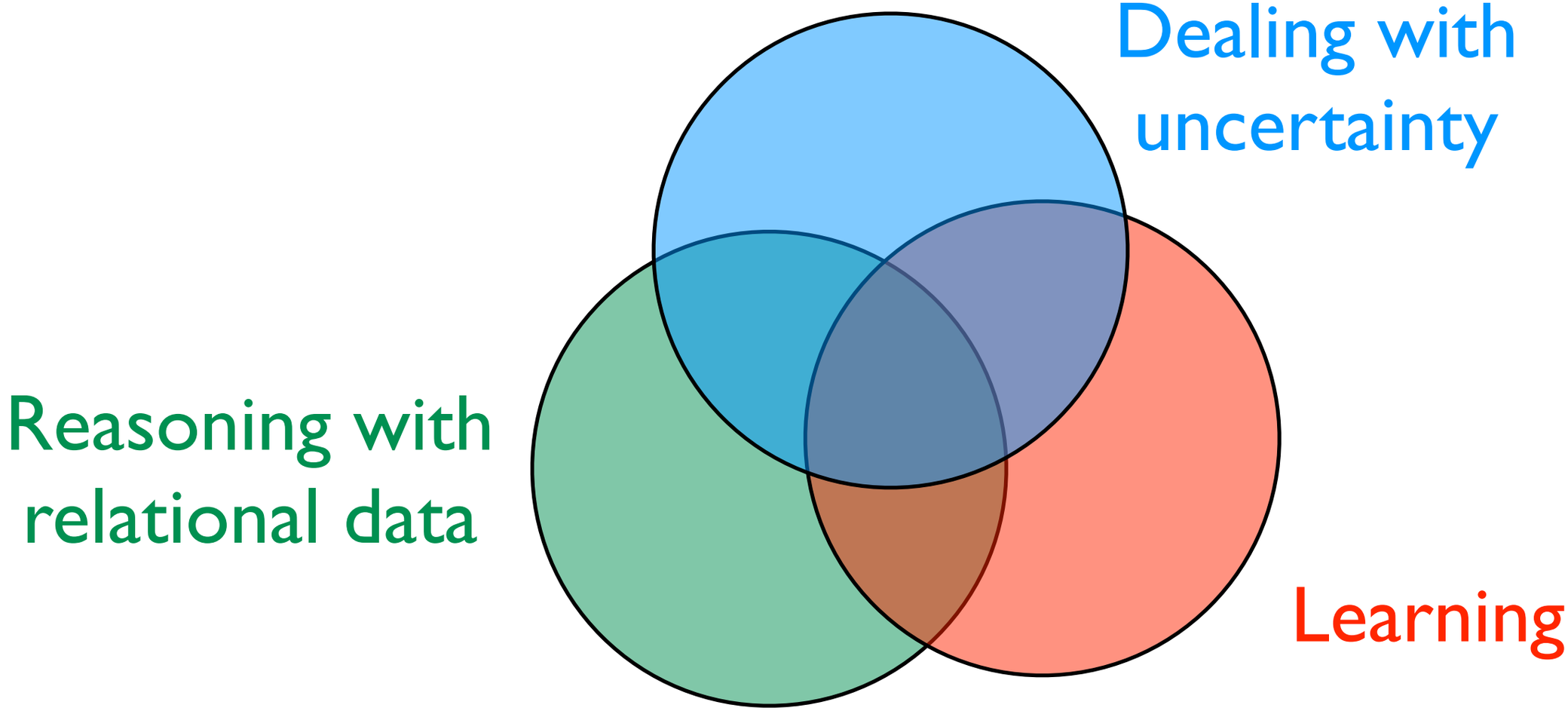
Biomine database @ Helsinki
http://biomine.cs.helsinki.fi/

This requires dealing with

- Structured environments
  - objects, and
  - relationships amongst them
- and possibly
  - using background knowledge
- cope with uncertainty
- learn from data

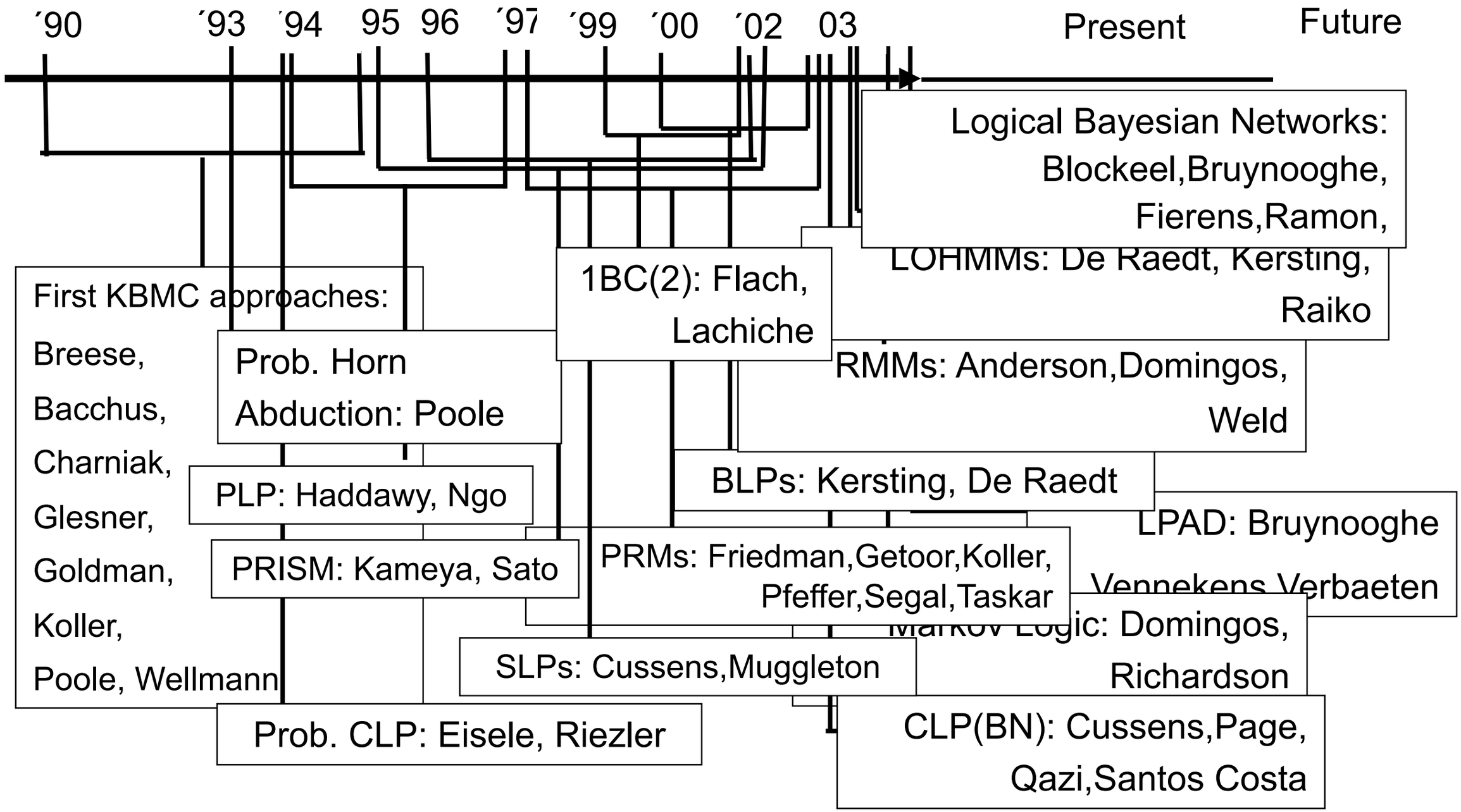
Statistical Relational Learning
Probabilistic Programming

Common theme

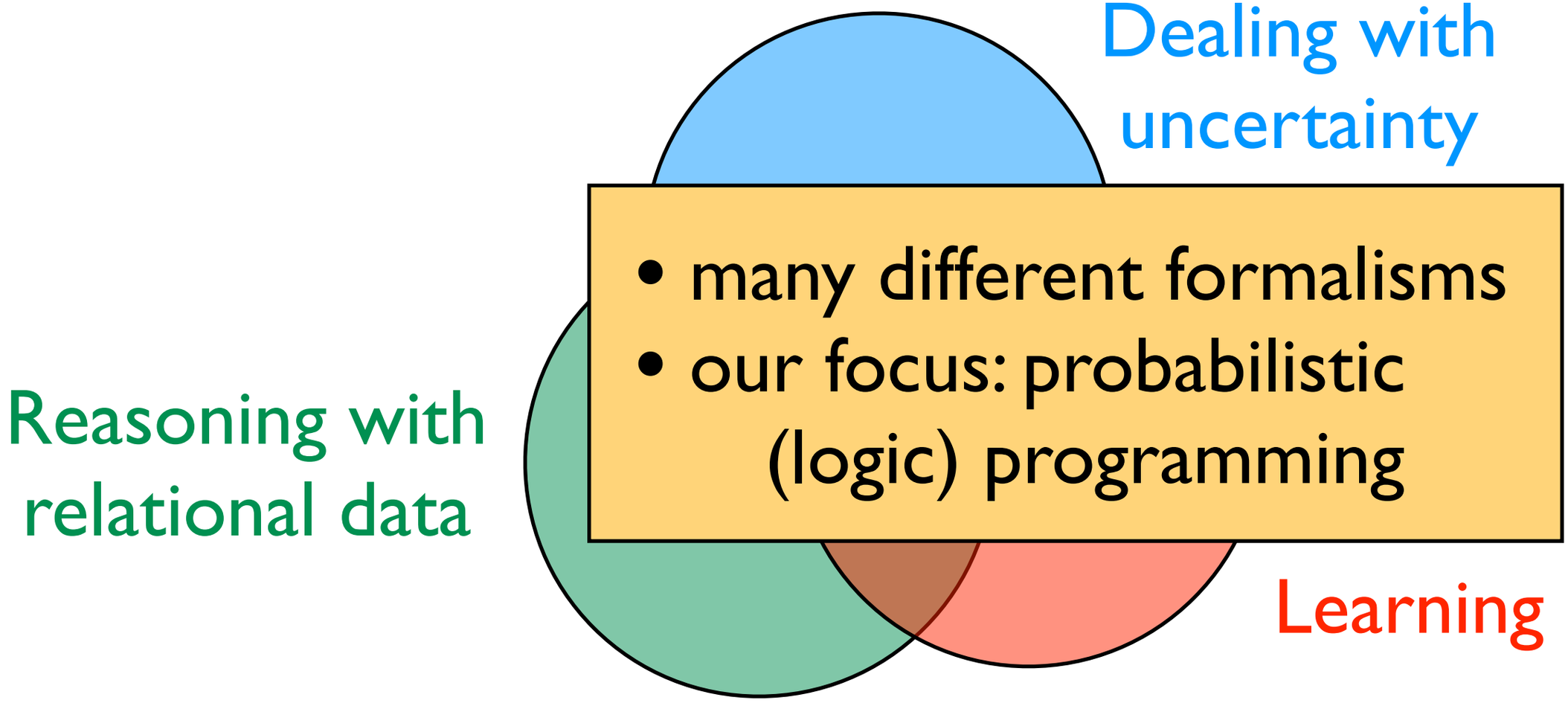


Statistical relational learning
& Probabilistic Programming, ...

Some formalisms



Common theme



Statistical relational learning
& Probabilistic Programming, ...

ProbLog

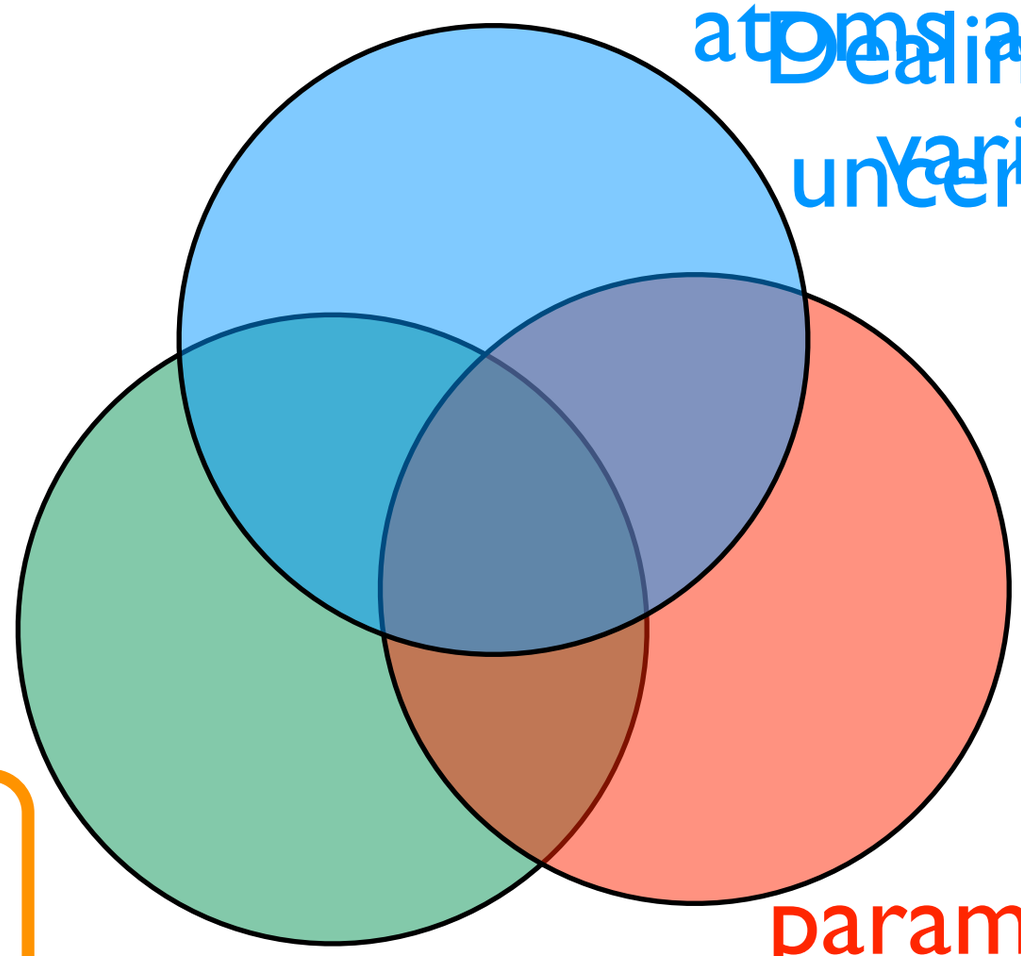
probabilistic Prolog

several possible worlds

```
0.8::stress(ann).
0.6::influences(ann,bob).
0.2::influences(bob,carl).
```

atoms as random variables

Dealing with uncertainty



Reasoning with probabilities

```
stress(ann).
influences(ann,bob).
influences(bob,carl).
```

one world

```
smokes(X) :- stress(X).
smokes(X) :-
     influences(Y,X), smokes(Y).
```

Learning parameter learning, adapted relational learning techniques

http://dtai.cs.kuleuven.be/problog/

Probabilistic Logic Programming

Distribution Semantics [Sato, ICLP 95]:
probabilistic choices + logic program
→ distribution over possible worlds

e.g., PRISM, ICL, ProbLog, LPADs, CP-logic, ...

- multi-valued switches
- probabilistic alternatives
- probabilistic facts
- annotated disjunctions
- causal-probabilistic laws

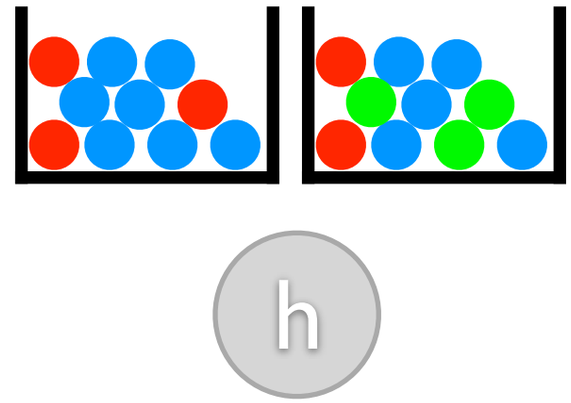
Roadmap

- Modeling (ProbLog and Church, another representative of PP)
- Inference
- Learning
- Dynamics and Decisions

... with some detours on the way

ProbLog by example:

A bit of gambling



- toss (biased) coin & draw ball from each urn
- win if (heads and a red ball) or (two balls of same color)

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
0.2 :: col(2,red); 0.3 :: col(2,green);
                   0.5 :: col(2,blue).

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

probabilistic fact: heads is true with probability 0.4 and false with 0.6)

annotated disjunction: first ball is red with probability 0.3 and blue with 0.7

annotated disjunction: second ball is red with probability 0.2, green with 0.3, and blue with 0.5

logical rule encoding background knowledge

consequences

Questions

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
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win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

marginal probability

- Probability of `win`?

query **conditional probability**

- Probability of `win` given `col(2,green)`?

evidence

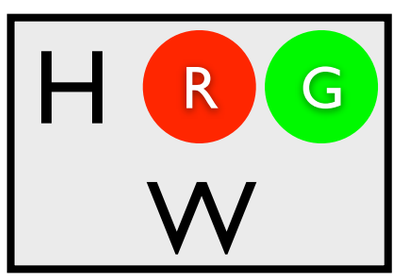
- Most probable world where `win` is true?

MPE inference

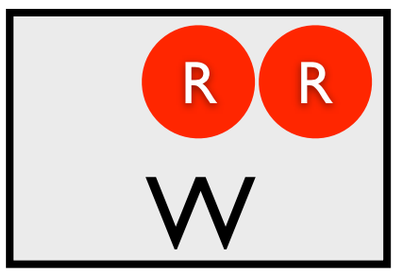
Possible Worlds

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue).
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue).

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

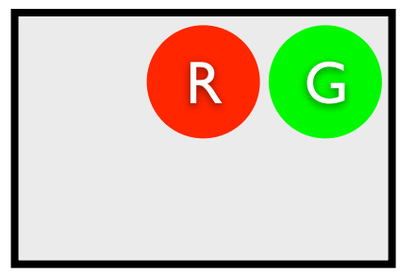
$0.4 \times 0.3 \times 0.3$



$(1-0.4) \times 0.3 \times 0.2$

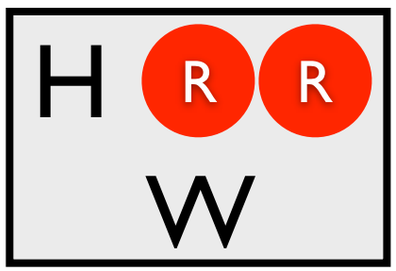


$(1-0.4) \times 0.3 \times 0.3$



All Possible Worlds

0.024



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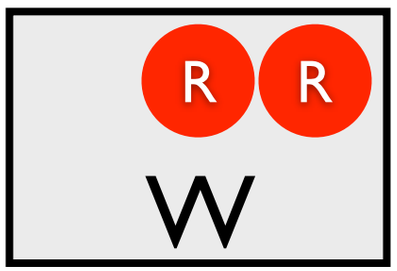

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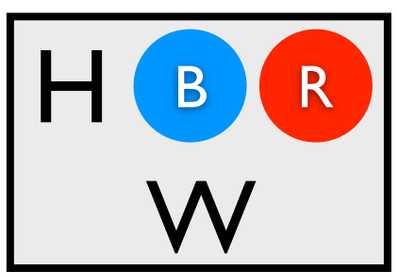

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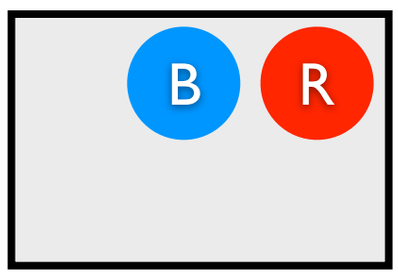

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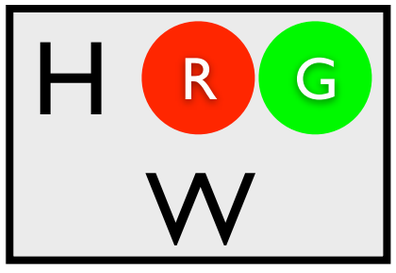

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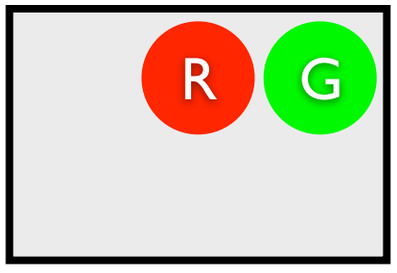

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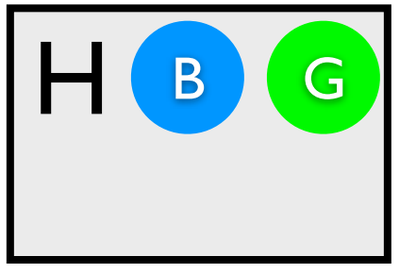

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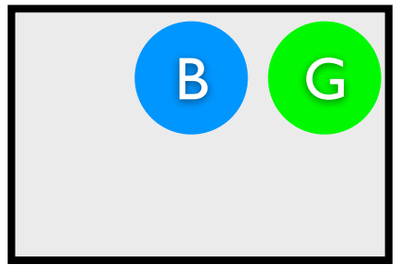

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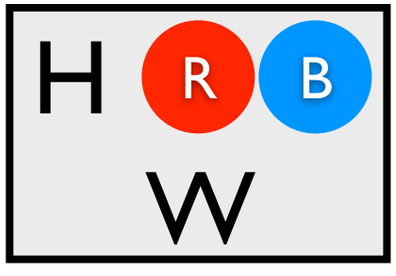

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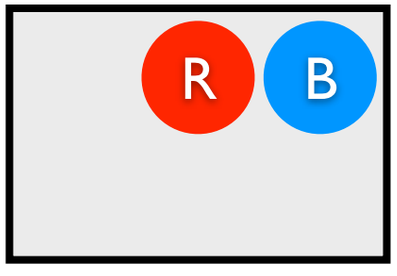

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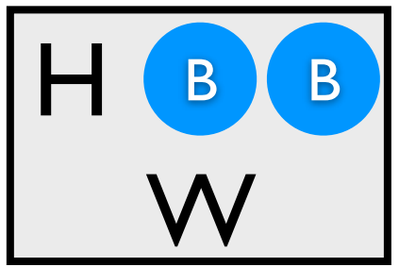

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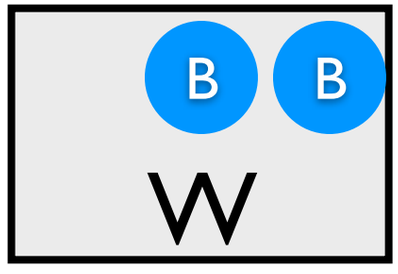
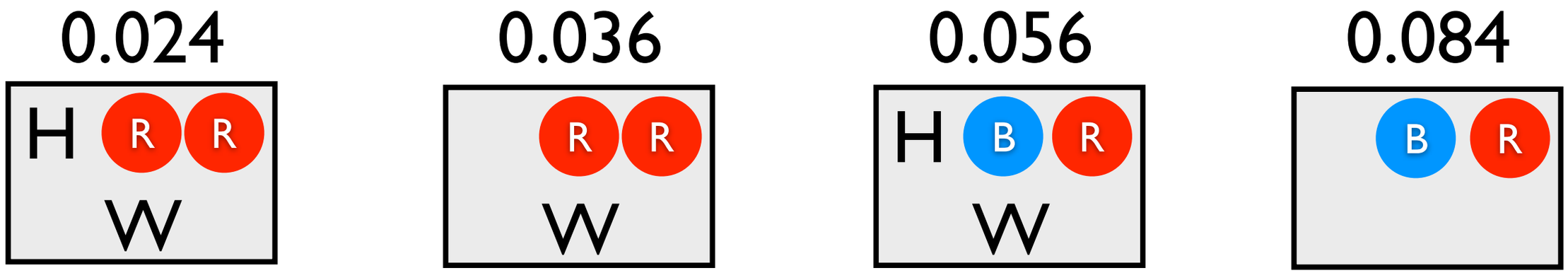


Most likely world where **win** is true?

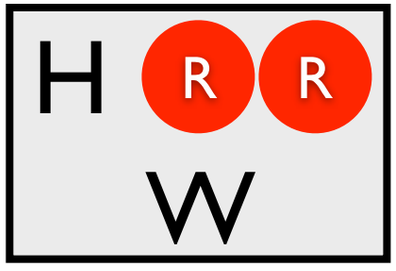
MPE Inference



Most likely world where `col(2,blue)` is false?

MPE Inference

0.024



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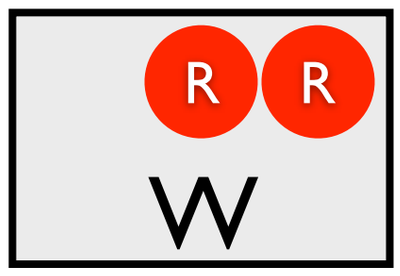

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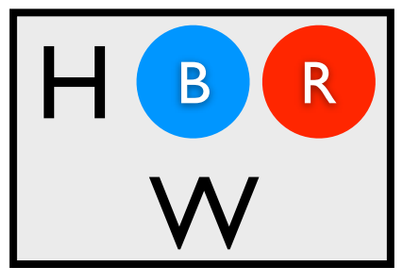

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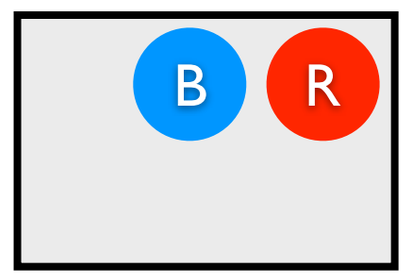

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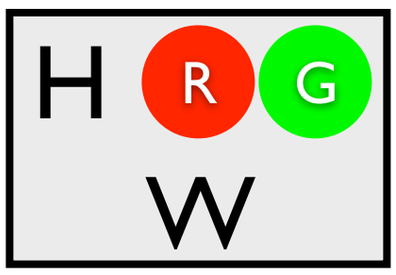

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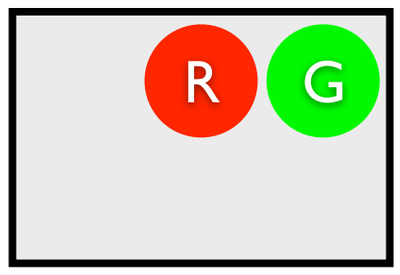

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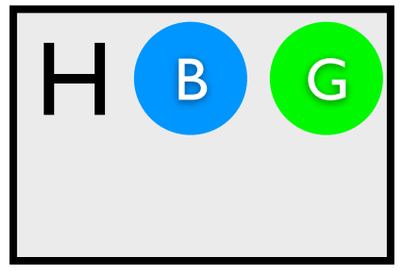

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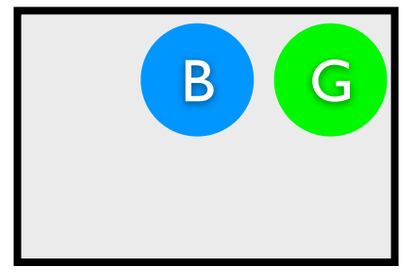

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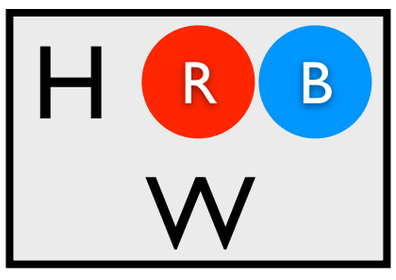
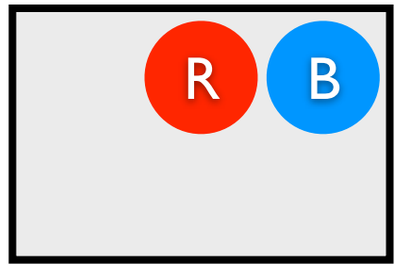
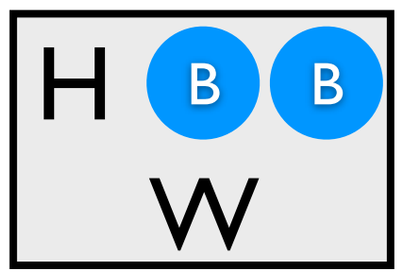


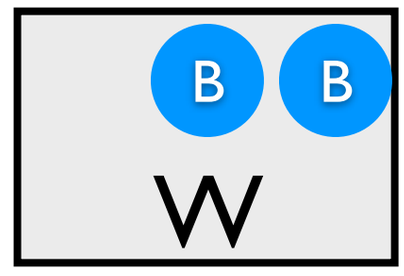
0.090



0.140

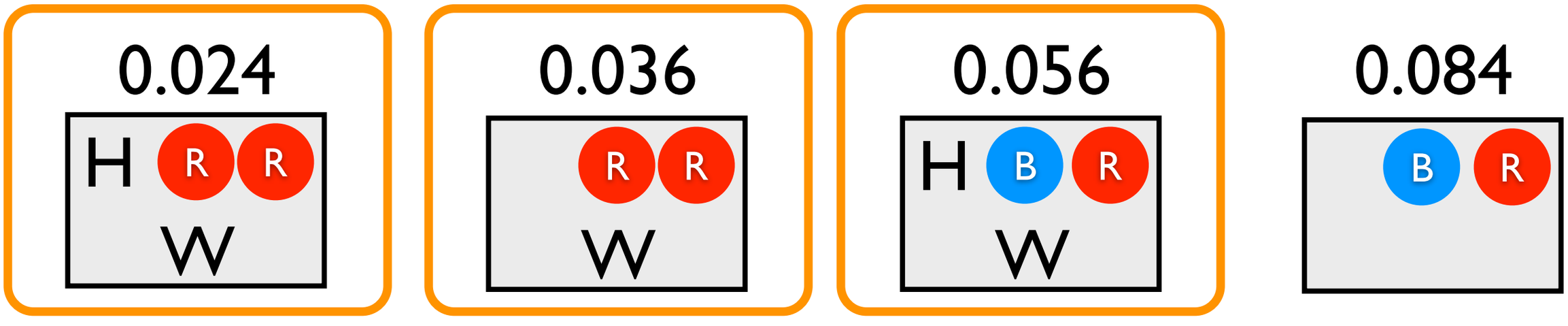


0.210



$$P(\underline{win}) = \underline{?\Sigma} = 0.562$$

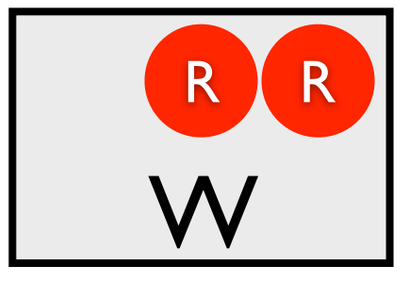
Marginal Probability

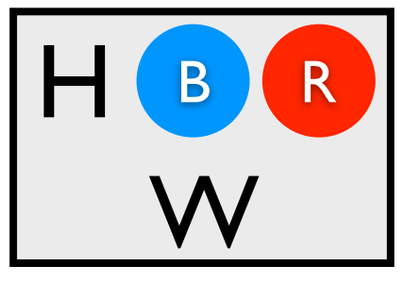


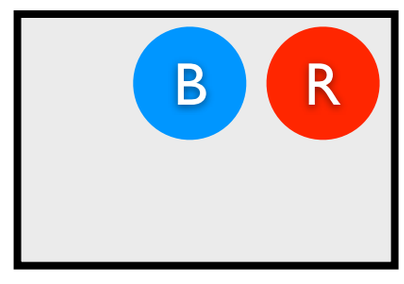
$$P(win|col(2,green)) = ?/\Sigma$$

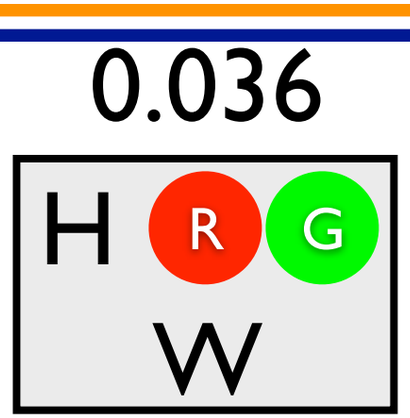
$$= P(win \wedge col(2,green)) / P(col(2,green))$$

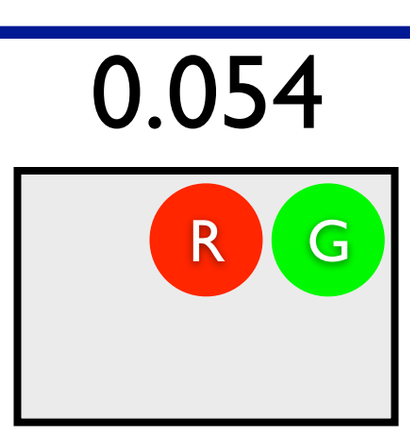
Conditional Probability

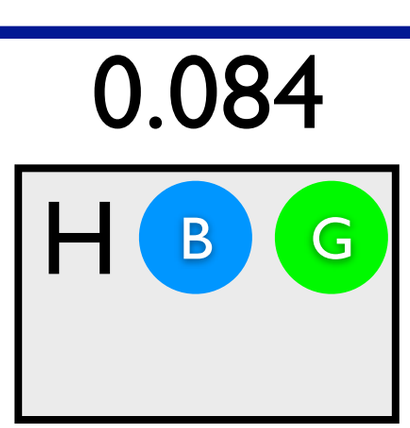


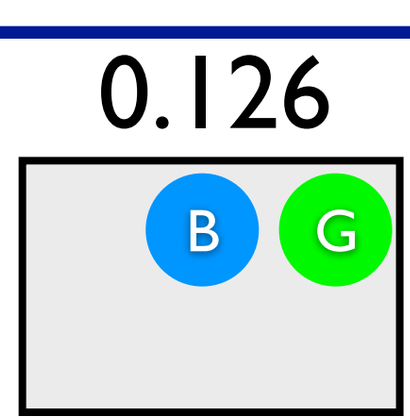


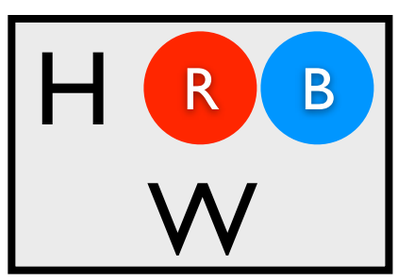


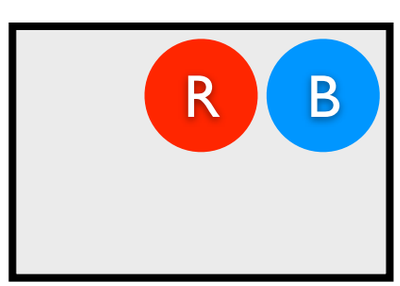


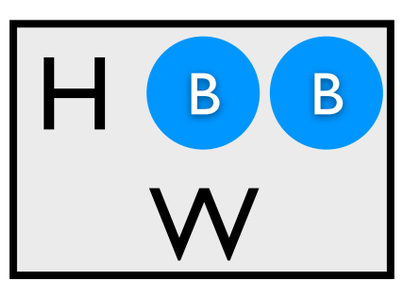


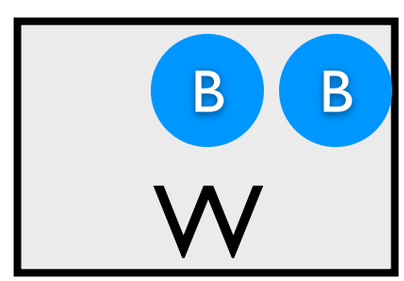












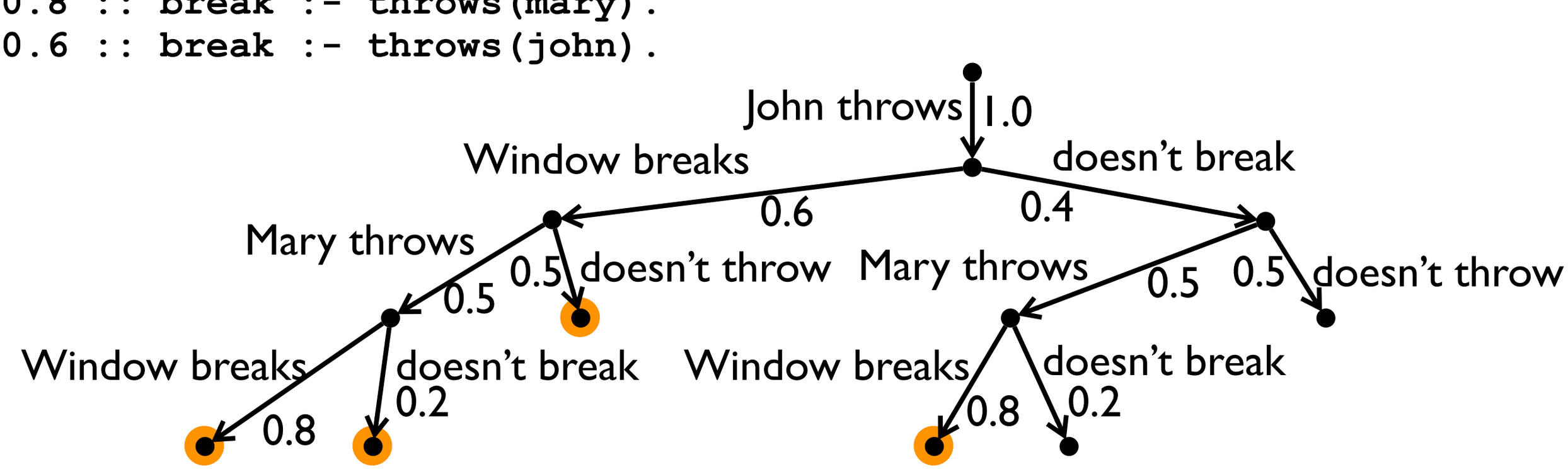
[Vennekens et al, ICLP 04]

Alternative view: CP-Logic

```
throws(john).
0.5::throws(mary).

0.8 :: break :- throws(mary).
0.6 :: break :- throws(john).
```

probabilistic causal laws



$$P(break)=0.6\times0.5\times0.8+0.6\times0.5\times0.2+0.6\times0.5+0.4\times0.5\times0.8$$

Distributional Clauses (DC)

Closely related to BLOG [Russell et al.]

- Discrete- and continuous-valued random variables

random variable with Gaussian distribution

```
length(Obj) ~ gaussian(6.0,0.45) :- type(Obj,glass).
stackable(OBot,OTop) :-
     ≃length(OBot) ≥ ≃length(OTop),
     ≃width(OBot) ≥ ≃width(OTop).
ontype(Obj,plate) ~ finite([0 : glass, 0.0024 : cup,
                            0 : pitcher, 0.8676 : plate,
                            0.0284 : bowl, 0 : serving,
                            0.1016 : none])
                          :- obj(Obj), on(Obj,O2), type(O2,plate).
```

comparing values of random variables

random variable with discrete distribution

[Gutmann et al, TPLP 11; Nitti et al, IROS 13]

Distributional Clauses (DC)

- Defines a generative process (as for CP-logic)
- Logic programming variant of Blog
- Tree can become infinitely wide
  - Sampling
- Well-defined under reasonable assumptions

[Suciu et al 2011]

Probabilistic Databases

several possible worlds

bornIn

person	city	P
ann	london	0,87
bob	york	0,95
		0,9
		0,56

cityIn

city	country	P
london	uk	0,99
york	uk	0,75
paris	usa	0,4

tuple-level uncertainty

probabilistic tables + database queries
→ distribution over possible worlds

```
select
from bornIn x, cityIn y
where x.city=y.city
```

one world

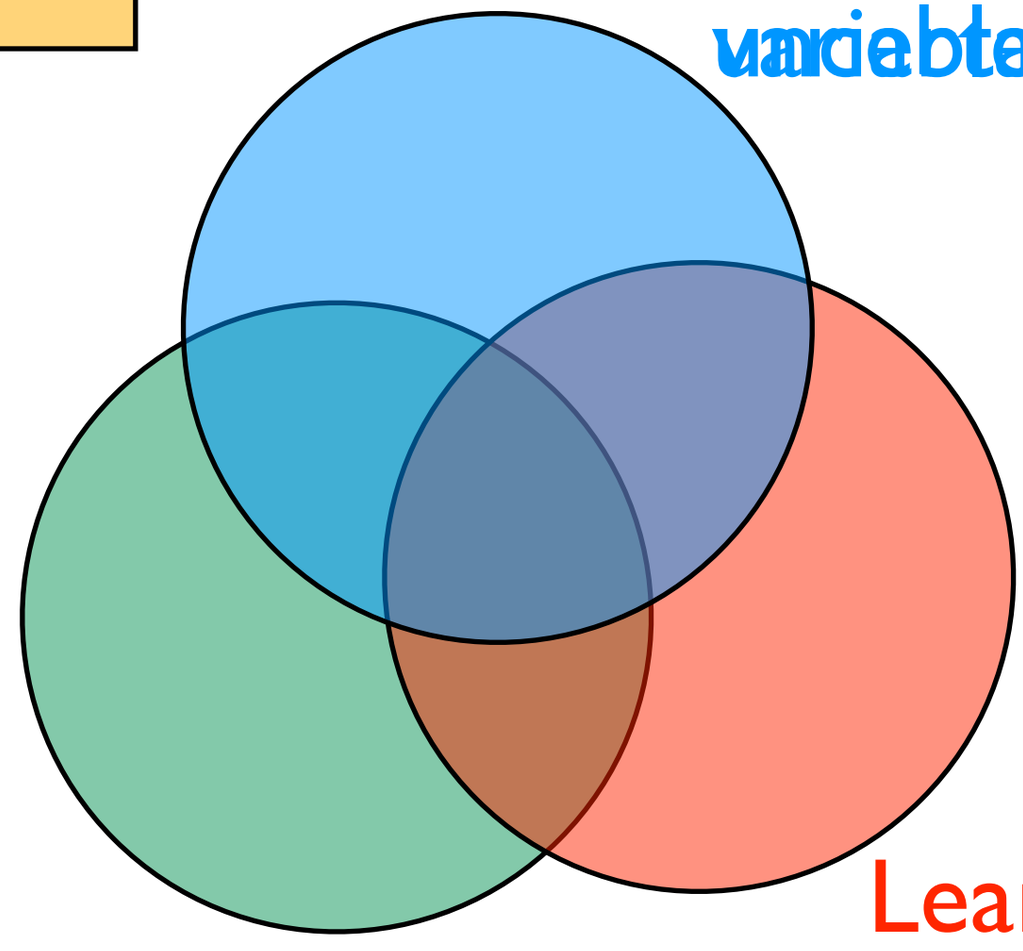
bornIn

person	city
ann	london
bob	york
eve	new york
tom	paris

cityIn

city	country
london	uk
york	uk
paris	usa

Reasoning with relational data



Example: Information Extraction

Recently-Learned Facts twitter

Refresh

instance	iteration	date learned	confidence
kelly_andrews is a female	826	29-mar-2014	98.7
investment_next_year is an economic sector	829	10-apr-2014	95.3
shibenik is a geopolitical entity that is an organization	829	10-apr-2014	97.2
quality_web_design_work is a character trait	826	29-mar-2014	91.0
mercedes_benz_cls_by_carlsson is an automobile manufacturer	829	10-apr-2014	95.2
social_work is an academic program at the university rutgers_university	827	02-apr-2014	93.8
dante wrote the book the_divine_comedy	826	29-mar-2014	93.8
willie_aames was born in the city los_angeles	831	16-apr-2014	100.0
kitt_peak is a mountain in the state or province arizona	831	16-apr-2014	96.9
greenwich is a park in the city london	831	16-apr-2014	100.0

instances for many different relations

degree of certainty

NELL: http://rtw.ml.cmu.edu/rtw/

Distribution Semantics

- **probabilistic choices** + their **consequences**
- probability distribution over **possible worlds**
- how to efficiently answer **questions**?
  - most probable world (MPE inference)
  - probability of query (computing marginals)
  - probability of query given evidence

Summary: ProbLog Syntax

- input database: ground facts

```
person(bob).
```

- probabilistic facts

```
0.5::stress(bob).
```

- annotated disjunctions

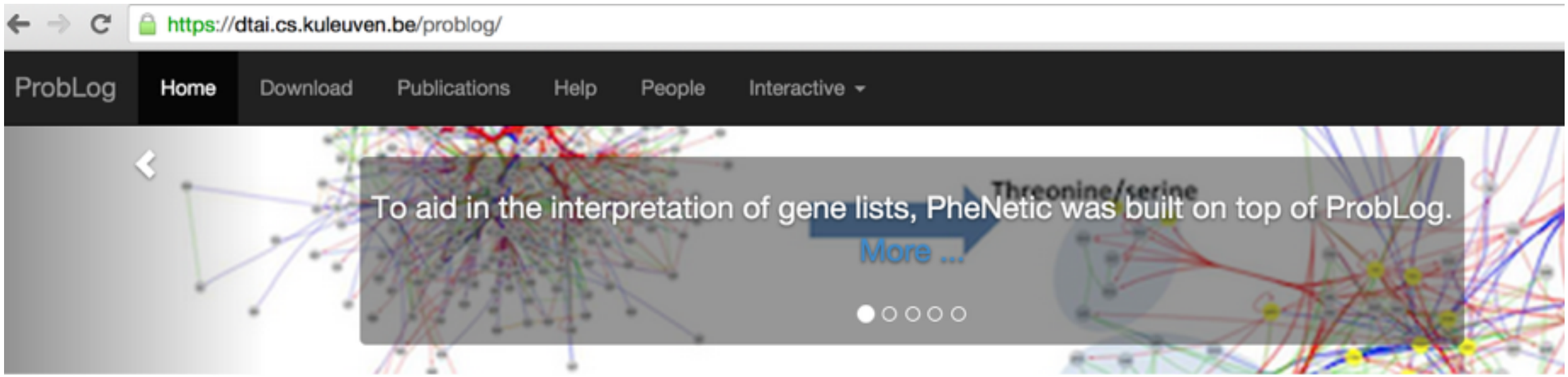
```
0.5::stress(X) :- person(X).
0.4::a(X); 0.3::b(X); 0.2::c(X); 0.1::d(X) :- q(X).
0.5::weather(sun,0) ; 0.5::weather(rain,0).
```

- flexible probabilities

```
P::pack(Item) :- weight(Item,W), P is 1.0/W.
```

- Prolog clauses

```
smokes(X) :- influences(Y,X), smokes(Y).
excess([I|R],Limit) :- \+pack(I), excess(R,Limit).
```



Introduction.

Probabilistic logic programs are logic programs in which some of the facts are annotated with probabilities.

ProbLog is a tool that allows you to intuitively build programs that do not only encode **complex interactions** between a large sets of **heterogenous components** bu **uncertainties** that are present in real-life situations.

The engine tackles several tasks such as computing the marginals given evidence and learning from (partial) interpretations. ProbLog is a suite of efficient algorithms tasks. It is based on a conversion of the program and the queries and evidence to a weighted Boolean formula. This allows us to reduce the inference tasks to well-s weighted model counting, which can be solved using state-of-the-art methods known from the graphical model and knowledge compilation literature.

The Language. Probabilistic Logic Programming.

ProbLog makes it easy to express complex, probabilistic models.

```
0.3::stress(X) :- person(X).
0.2::influences(X,Y) :- person(X), person(Y).

smokes(X) :- stress(X).
smokes(X) :- friend(X,Y), influences(Y,X), smokes(Y).
```

Some Probabilistic Programming Languages outside LP

- IBAL [Pfeffer 01]
- Figaro [Pfeffer 09]
- Church [Goodman et al 08]
- BLOG [Milch et al 05]
- Venture [Mansingha et al.]
- Anglican and Probabilistic-C [Wood et al].
- and many more appearing recently

Church

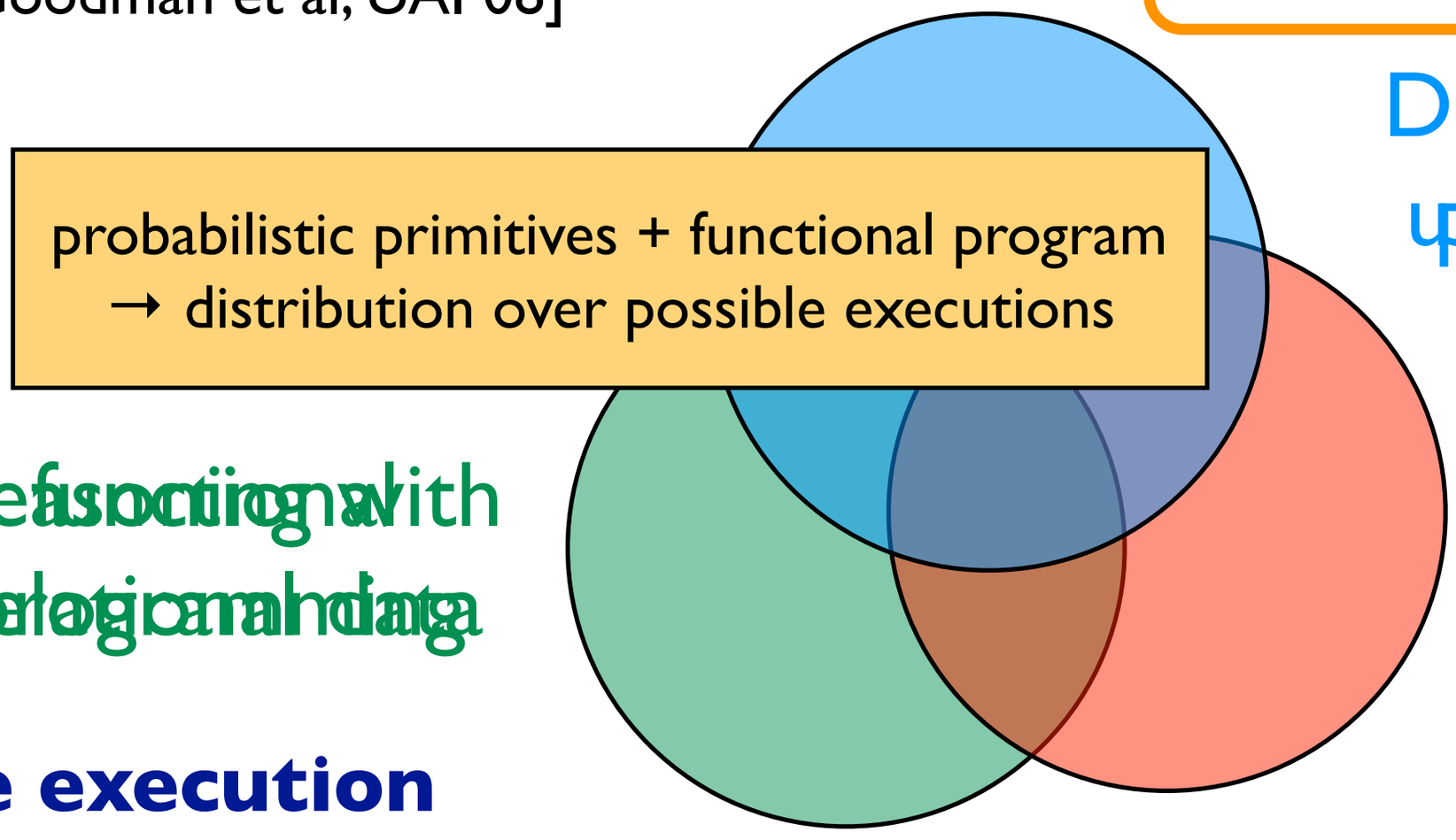
probabilistic functional programming

[Goodman et al, UAI 08]

several possible executions

```
(define randplus5
 (lambda (x) (if (flip 0.6)
                 (+ x 5)
                 x)))

(map randplus5 '(1 2 3))
```



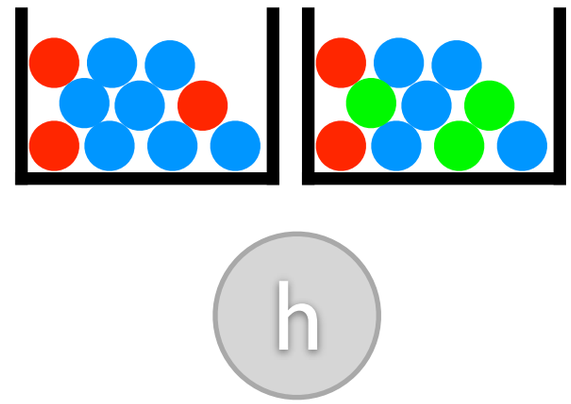
one execution

```
(define plus5 (lambda (x) (+ x 5)))

(map plus5 '(1 2 3))
```

Church by example:

A bit of gambling



- toss (biased) coin & draw ball from each urn
- win if (heads and a red ball) or (two balls of same color)

```
(define heads (mem (lambda () (flip 0.4))))

(define color1 (mem (lambda () (if (flip 0.3) 'red 'blue))))

(define color2 (mem (lambda ()
                      (multinomial '(red green blue) '(0.2 0.3 0.5)))))

(define redball (or (equal? (color1) 'red) (equal? (color2) 'red)))

(define win1 (and (heads) redball))

(define win2 (equal? (color1) (color2)))

(define win (or win1 win2))
```

Probabilistic Programming Summary

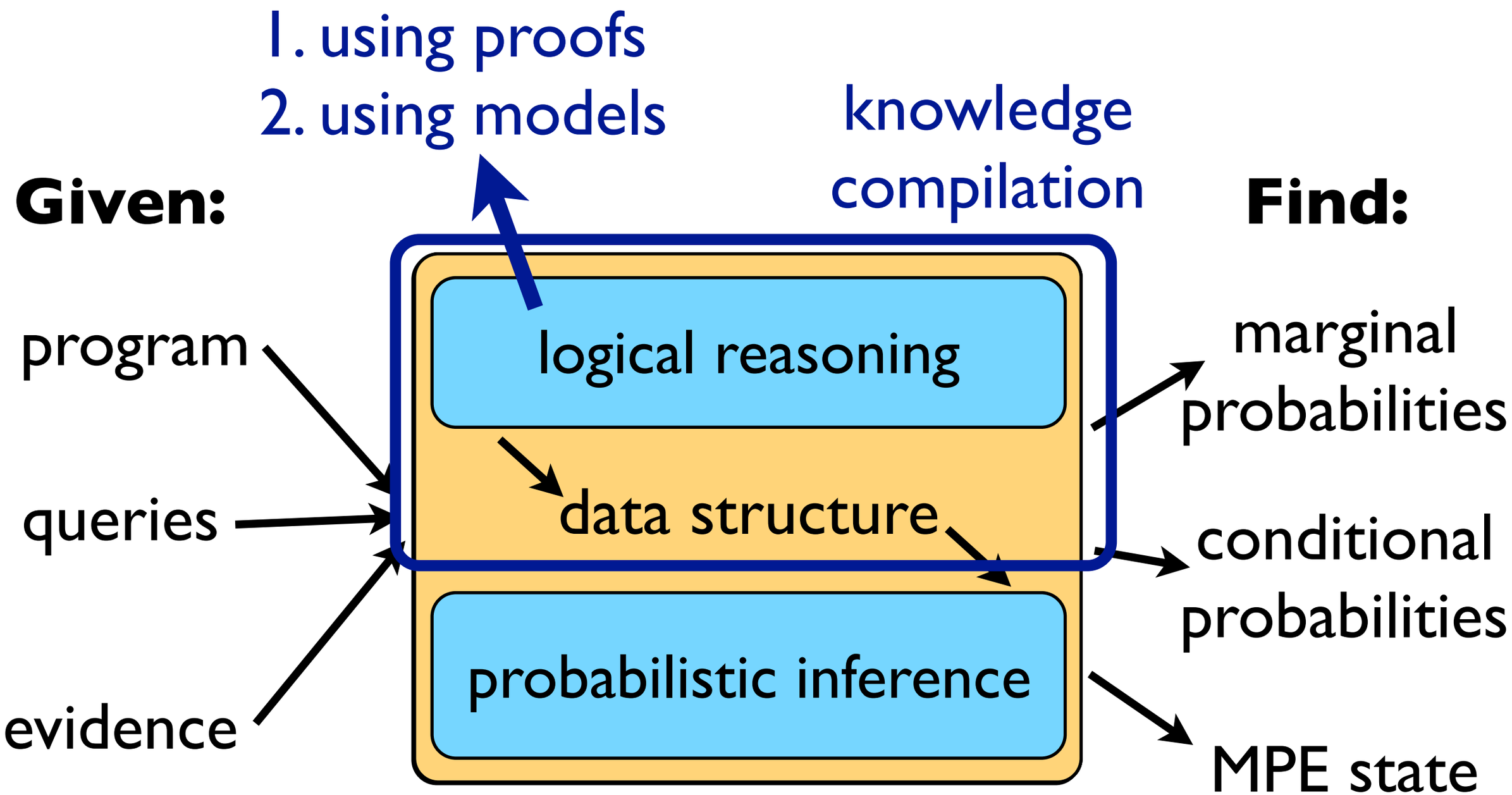
- Church: functional programming + random primitives
- probabilistic generative model
- stochastic memoization
- sampling
- increasing number of probabilistic programming languages using various underlying paradigms

Roadmap

- Modeling (ProbLog and Church, another representative of PP)
- **Inference**
- Learning
- Dynamics and Decisions

... with some detours on the way

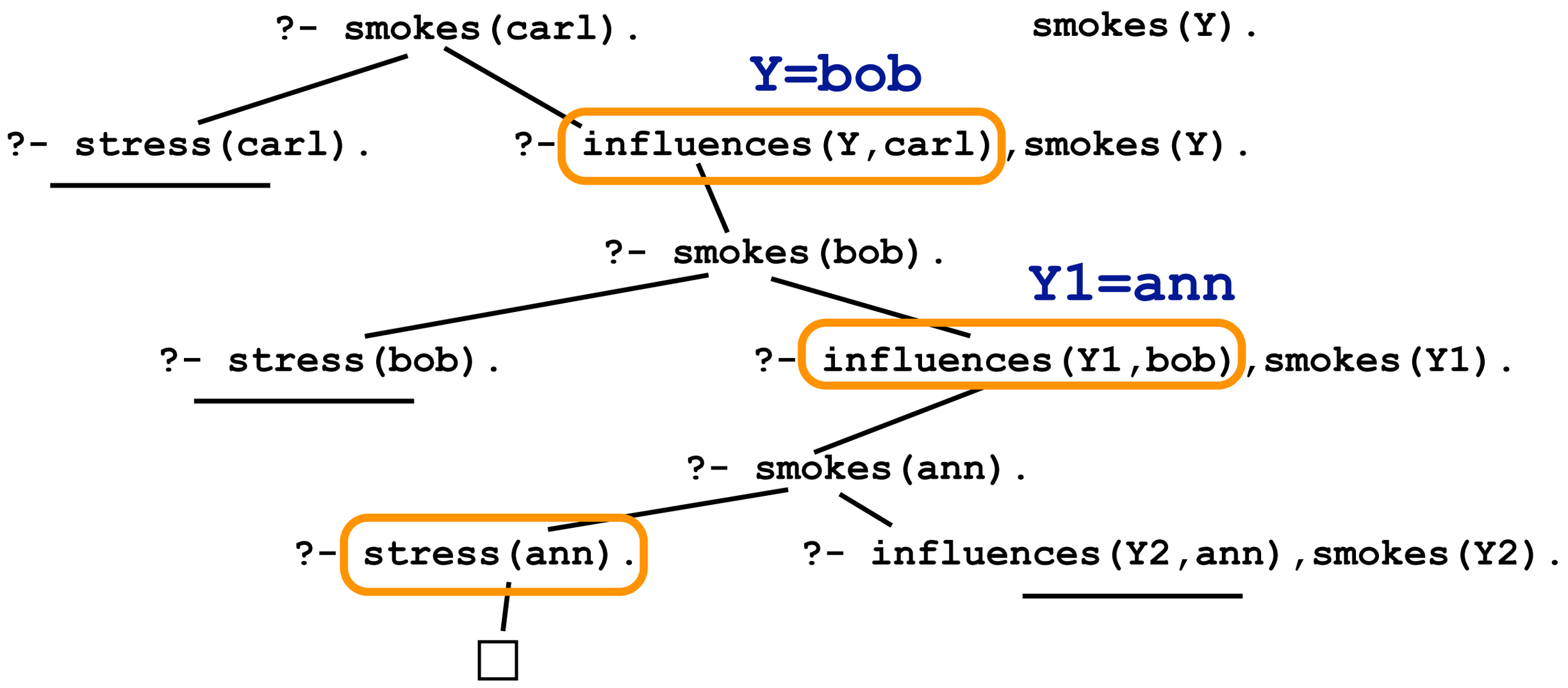
Answering Questions



Proofs in ProbLog

```
0.8::stress(ann).
0.6::influences(ann,bob).
0.2::influences(bob,carl).

smokes(X) :- stress(X).
smokes(X) :-
     influences(Y,X),
     smokes(Y).
```



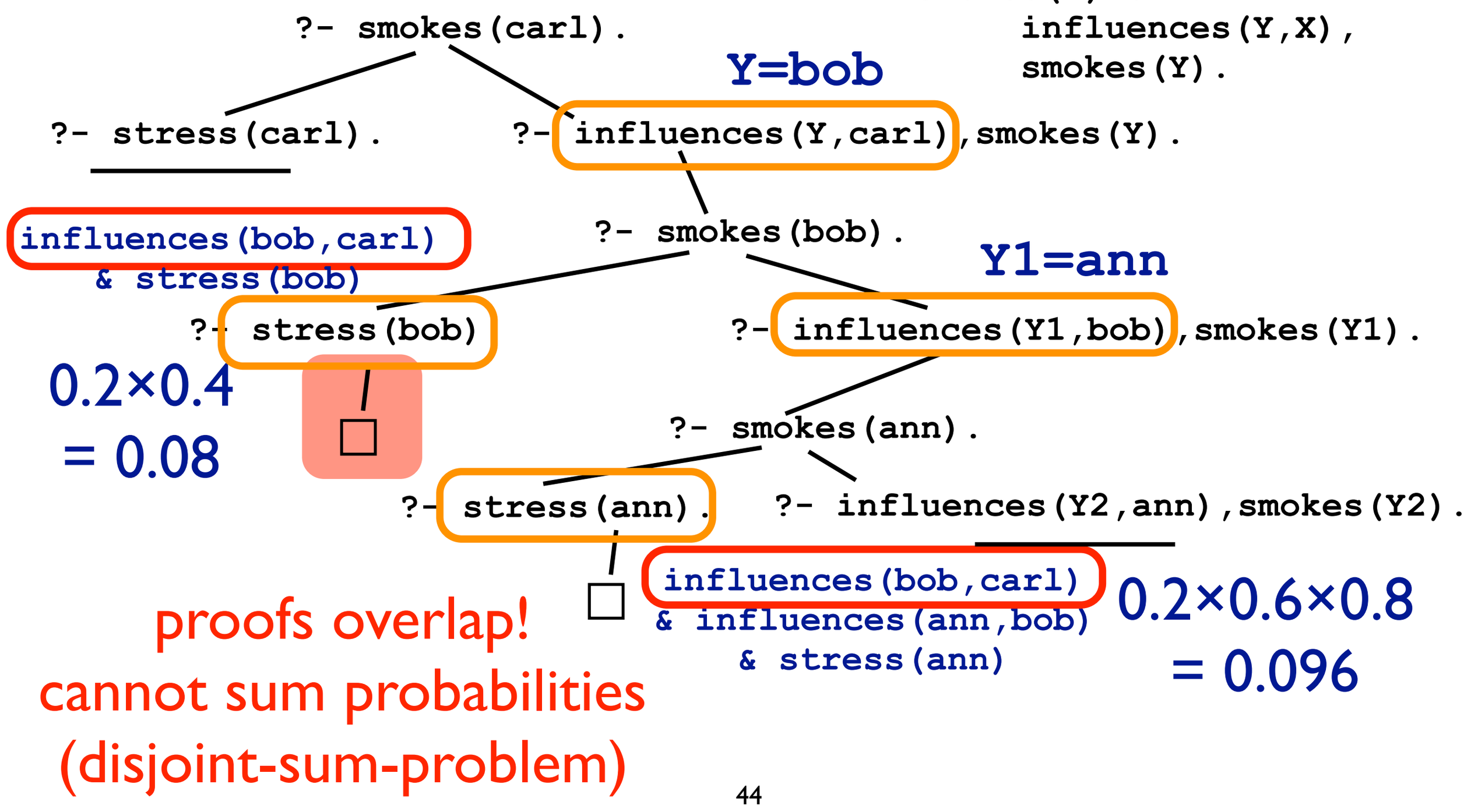
`influences(bob,carl)&influences(ann,bob)&stress(ann)`

probability of proof = 0.2 × 0.6 × 0.8 = 0.096

Proofs in ProbLog

```
0.8::stress(ann).
0.4::stress(bob).
0.6::influences(ann,bob).
0.2::influences(bob,carl).

smokes(X) :- stress(X).
smokes(X) :-
     influences(Y,X),
     smokes(Y).
```



Disjoint-Sum-Problem

possible worlds

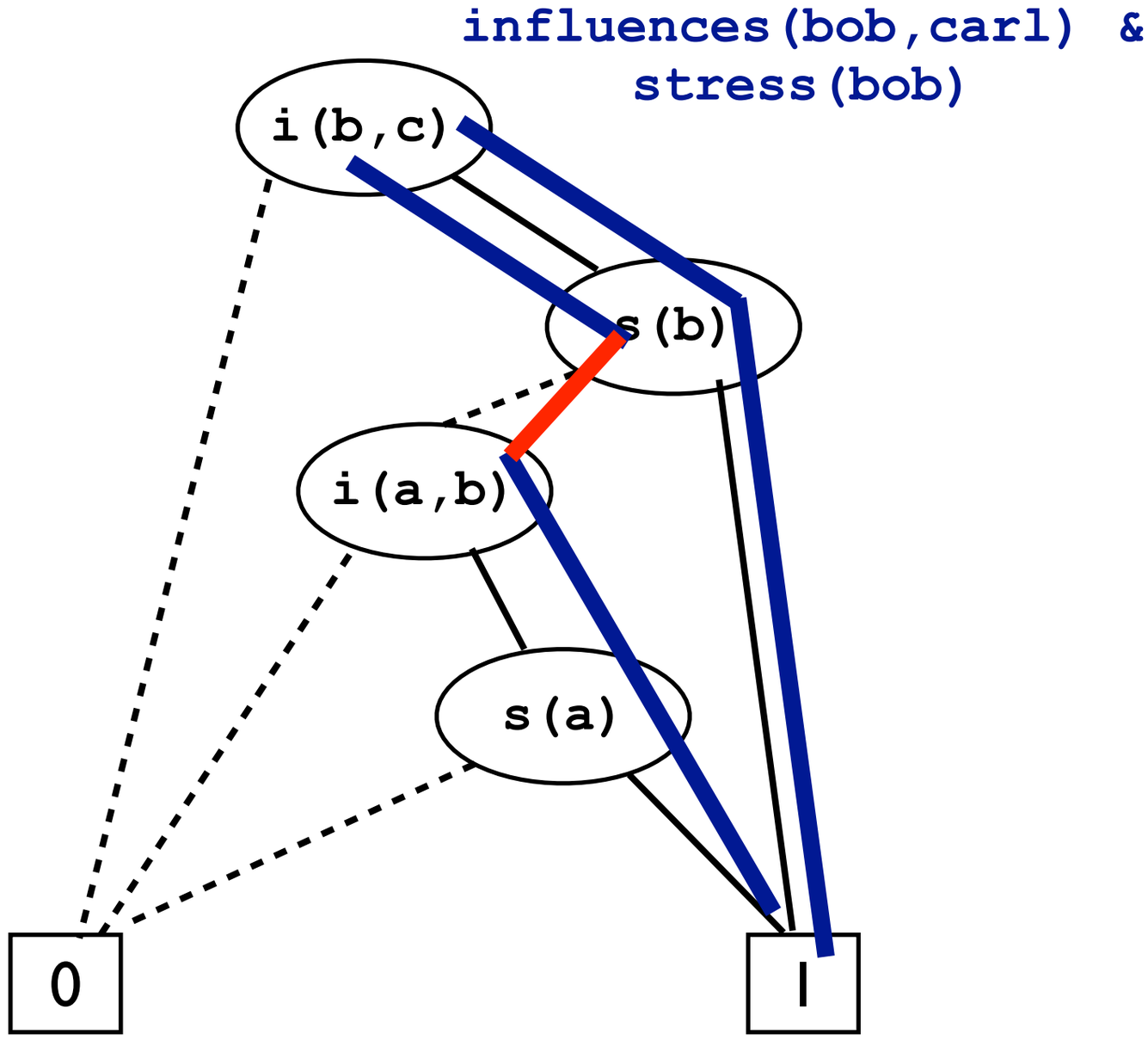
solution: knowledge compilation

`infl(bob,carl) & infl(ann,bob) & st(ann) & \+st(bob)`	0.0576
`infl(bob,carl) & infl(ann,bob) & st(ann) & st(bob)`	0.0384
`infl(bob,carl) & \+infl(ann,bob) & st(ann) & st(bob)`	0.0256
`infl(bob,carl) & infl(ann,bob) & \+st(ann) & st(bob)`	0.0096
`infl(bob,carl) & \+infl(ann,bob) & \+st(ann) & st(bob)`	0.0064
`...` `influences(bob,carl) & stress(bob)`	$\sum = 0.1376$

sum of proof probabilities: 0.096+0.08 = 0.1760

Binary Decision Diagrams [Bryant 86]

- compact graphical representation of Boolean formula
- automatically disjoins proofs
- popular in many branches of CS



Binary Decision Diagrams [Bryant 86]

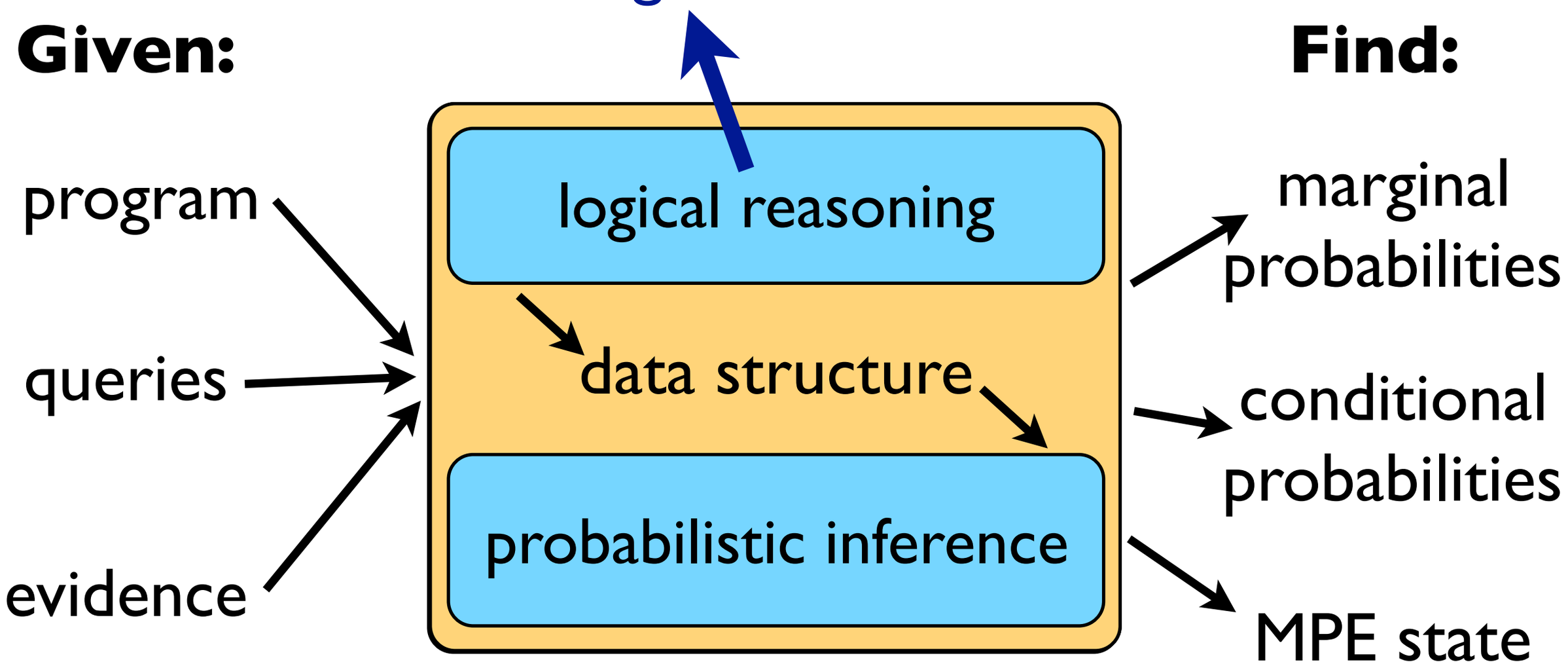
- compact graphical representation of Boolean formula
- popular in many branches of CS
- automatically disjoins proofs
  → efficient probability computation
- other representations exist (SDDs, d-DNNFs)
- knowledge compilation is state of the art for probabilistic inference (Darwiche et al.)

Answering Questions

1. using proofs
2. using models

Given:

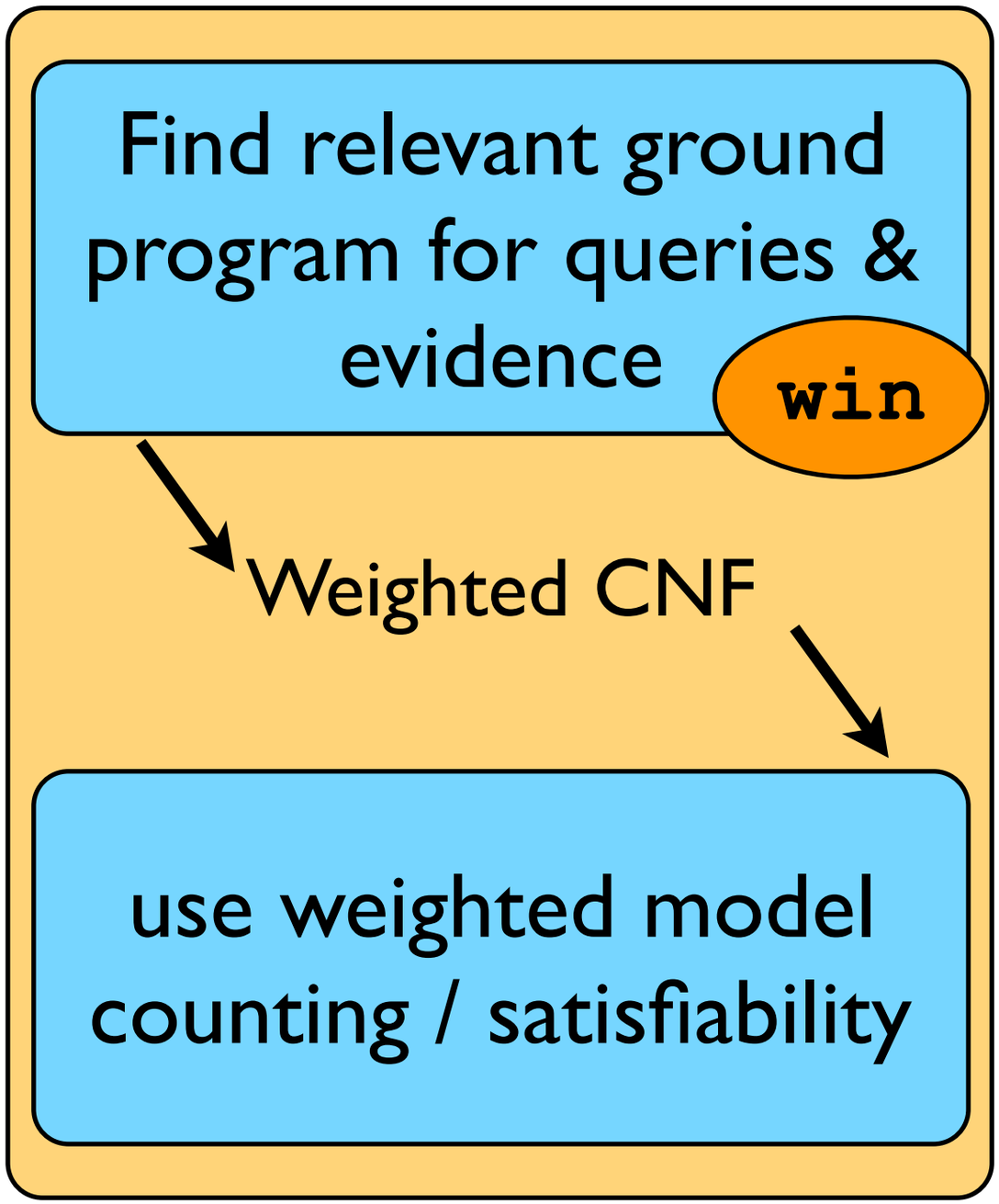
Find:



Current Approach

(ProbLog2)

```
0.4::heads(1).
0.7::heads(2).
0.5::heads(3).
win :- heads(1).
win :- heads(2),
       heads(3).
```




```
win :- heads(1).
win :- heads(2), heads(3).
```

$$\text{win} \leftrightarrow h(1) \vee (h(2) \wedge h(3))$$

$$(\neg\text{win} \vee h(1) \vee h(2)) \wedge (\neg\text{win} \vee h(1) \vee h(3)) \wedge (\text{win} \vee \neg h(1)) \wedge (\text{win} \vee \neg h(2) \vee \neg h(3))$$

use standard solver

$h(1) \rightarrow 0.4$	$h(2) \rightarrow 0.7$	$h(3) \rightarrow 0.5$
$\neg h(1) \rightarrow 0.6$	$\neg h(2) \rightarrow 0.3$	$\neg h(3) \rightarrow 0.5$

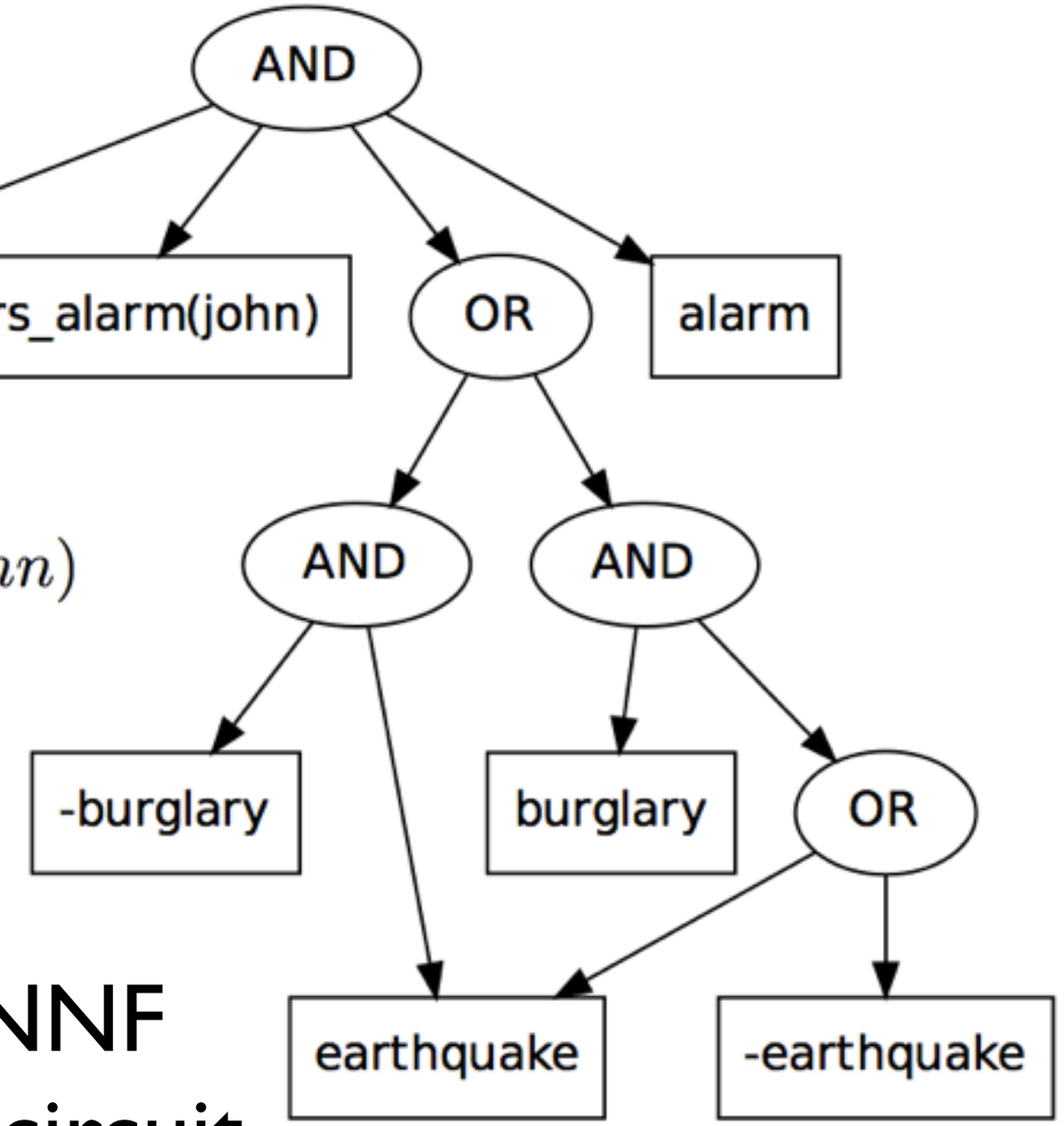
[Fierens et al, TPLP 14]

WMC using d-DNNFs

$$alarm \leftrightarrow burglary \vee earthquake$$

$$calls(john) \leftrightarrow alarm, hears\_alarm(john)$$

$$calls(john)$$



1. represent formula as d-DNNF
2. transform into arithmetic circuit
3. evaluate bottom-up

[Figure: Fierens et al, TPLP 14]

Markov Chain Monte Carlo (MCMC)

- Generate next sample by modifying current one
- Most common inference approach for PP languages such as Church, BLOG, ...
- Also considered for PRISM and ProbLog

Key challenges:
- how to propose next sample
- how to handle evidence

Roadmap

- Modeling (ProbLog and Church, another representative of PP)
- Inference
- **Learning**
- Dynamics and Decisions

... with some detours on the way

Parameter Learning

e.g., webpage classification model

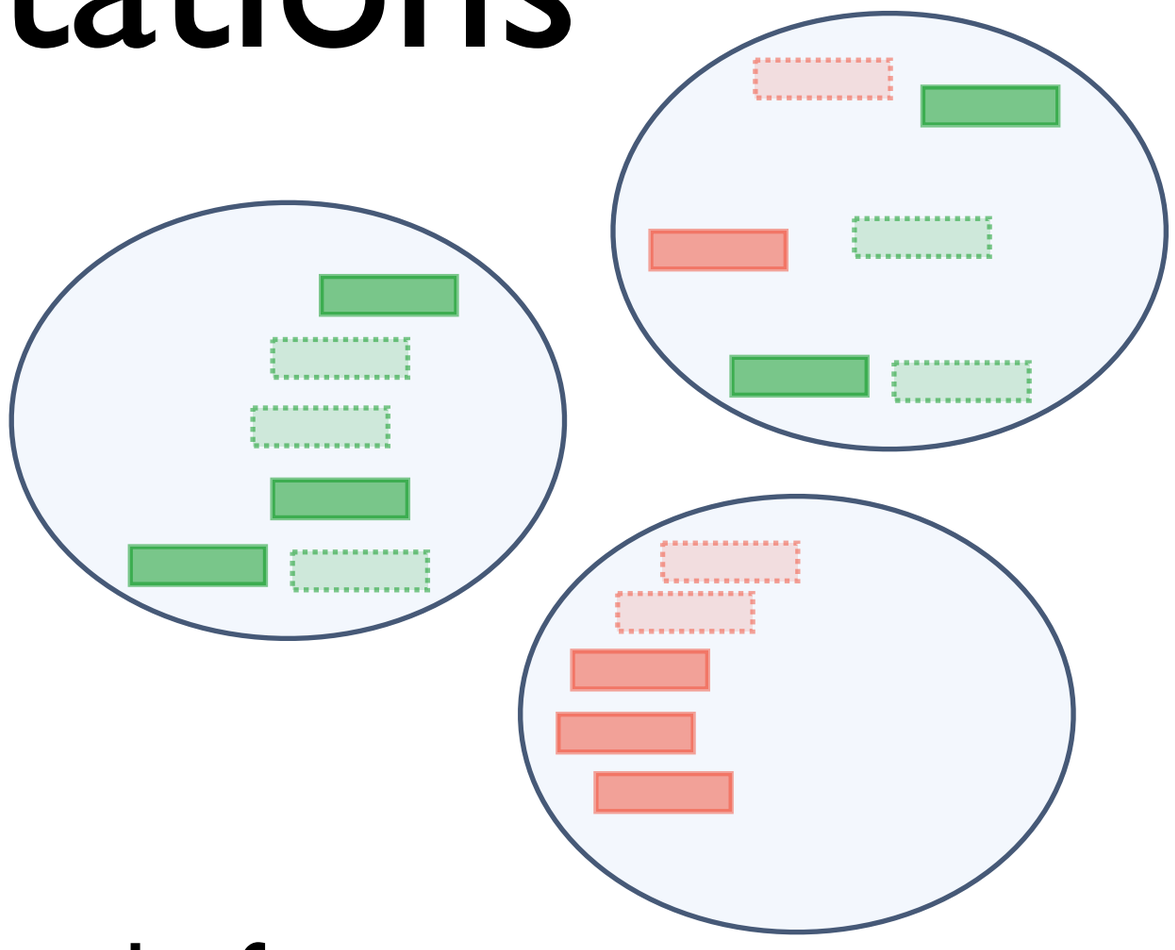
for each *CLASS1*, *CLASS2* and each *WORD*

?? :: link_class(Source,Target,*CLASS1*,*CLASS2*).
?? :: word_class(*WORD*,*CLASS*).

```
class(Page,C)    :-  has_word(Page,W), word_class(W,C).

class(Page,C)        :-  links_to(OtherPage,Page),
    class(OtherPage,OtherClass),
                         link_class(OtherPage,Page,OtherClass,C).
```

Learning from partial interpretations



- Not all facts observed
- Soft-EM
- use **expected count** instead of **count**
- **P(Q |E) -- conditional queries !**

[Gutmann et al, ECML 11; Fierens et al, TPLP 14]

Rule learning — NELL

Table 5: Number of facts per predicate (NELL athlete dataset)

athletecoach(person,person)	18	athleteplaysforteam(person,team)	721
athleteplayssport(person,sport)	1921	teamplaysinleague(team,league)	1085
athleteplaysinleague(person,league)	872	athletealsoknownas(person,name)	17
coachesinleague(person,league)	93	coachesteam(person,team)	132
teamhomestadium(team,stadium)	198	teamplayssport(team,sport)	359
athleteplayssportsteamposition(person,position)	255	athletehomestadium(person,stadium)	187
athlete(person)	1909	attraction(stadium)	2
coach(person)	624	female(person)	2
male(person)	7	hobby(sport)	5
organization(league)	1	person(person)	2
personafrica(person)	1	personasia(person)	4
personaustralia(person)	22	personcanada(person)	1
personeurope(person)	1	personmexico(person)	108
personus(person)	6	sport(sport)	36
sportsleague(league)	18	sportsteam(team)	1330
sportsteamposition(position)	22	stadiumoreventvenue(stadium)	171

Adaptation of standard rule learning and inductive logic programming setting
[De Raedt et al IJCAI 15]

Experiments

Table 4: Precision for different experimental setups and parameters (A: $m = 1, p = 0.99$, B: $m = 1000, p = 0.90$).

Setting	**athleteplaysforteam**		**athleteplayssport**		**teamplaysinleague**		**athleteplaysinleague**		**teamplaysagainstteam**	
train/test/rule	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**
1: det/det/det	74.00	69.36	94.14	93.47	96.29	82.15	80.95	74.14	73.40	73.86
2: det/prob/det	73.51	69.57	97.53	94.85	96.70	87.83	90.83	77.73	73.70	73.35
3: det/prob/prob	74.67	69.82	95.86	94.74	96.35	82.57	82.26	75.29	73.84	74.34
4: det/prob/prob	77.25	73.87	96.53	96.04	98.00	90.59	84.91	79.36	77.26	77.83
5: det/prob/prob	74.76	69.97	95.85	94.69	96.44	82.51	81.99	75.07	73.90	74.16
6: prob/prob/det	75.83	73.11	93.40	93.76	94.44	93.67	79.41	79.42	80.87	80.60
7: prob/prob/prob	78.31	73.72	95.62	95.10	98.84	91.86	96.94	79.49	85.78	81.81

Table 3: Learned relational rules for the different predicates (fold 1).

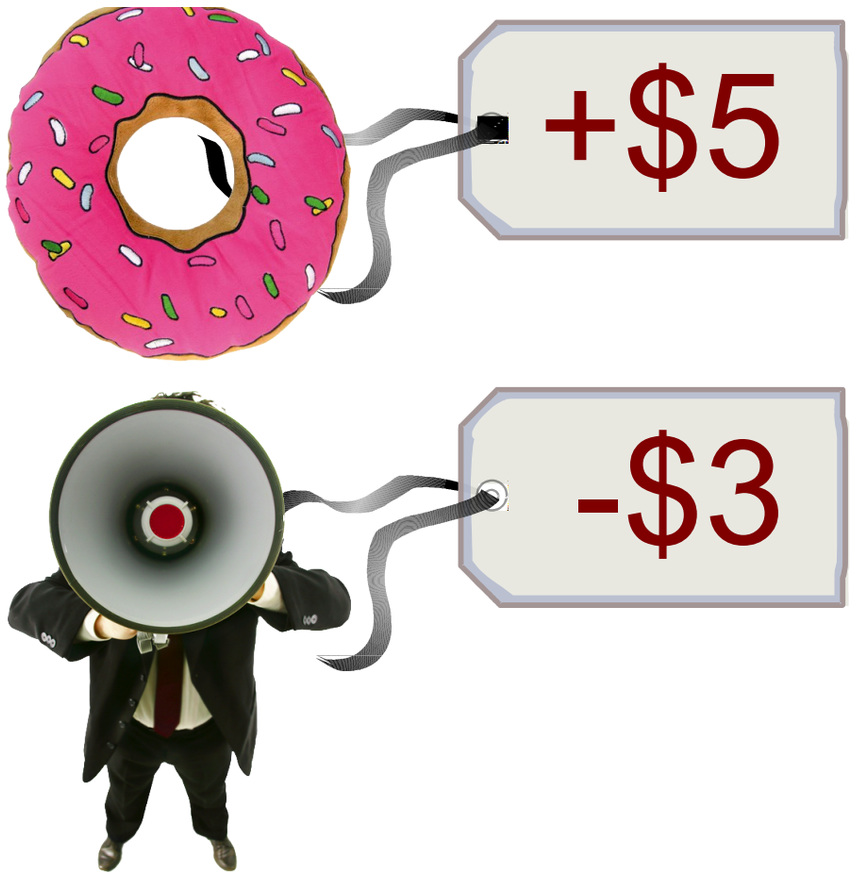
0.9375::athleteplaysforteam(A,B)	←	athleteledsportsteam(A,B).
0.9675::athleteplaysforteam(A,B)	←	athleteledsportsteam(A,V1), teamplaysagainstteam(B,V1).
0.9375::athleteplaysforteam(A,B)	←	athleteplayssport(A,V1), teamplayssport(B,V1).
0.5109::athleteplaysforteam(A,B)	←	athleteplaysinleague(A,V1), teamplaysinleague(B,V1).
0.9070::athleteplayssport(A,B)	←	athleteledsportsteam(A,V2), teamalsoknownas(V2,V1), teamplayssport(V1,B), teamplayssport(V2,B).
0.9070::athleteplayssport(A,B)	←	athleteplaysforteam(A,V2), teamalsoknownas(V2,V1), teamplayssport(V1,B), teamplayssport(V2,B),teamalsoknownas(V1,V2).
0.9070::athleteplayssport(A,B)	←	athleteplaysforteam(A,V1), teamplayssport(V1,B).
0.9286::athleteplaysinleague(A,B)	←	athleteledsportsteam(A,V1), teamplaysinleague(V1,B).
0.7868::athleteplaysinleague(A,B)	←	athleteplaysforteam(A,V2), teamalsoknownas(V2,V1), teamplaysinleague(V1,B).
0.9384::athleteplaysinleague(A,B)	←	athleteplayssport(A,V2), athleteplayssport(V1,V2), teamplaysinleague(V1,B).
0.9024::athleteplaysinleague(A,B)	←	athleteplaysforteam(A,V1), teamplaysinleague(V1,B).

Roadmap

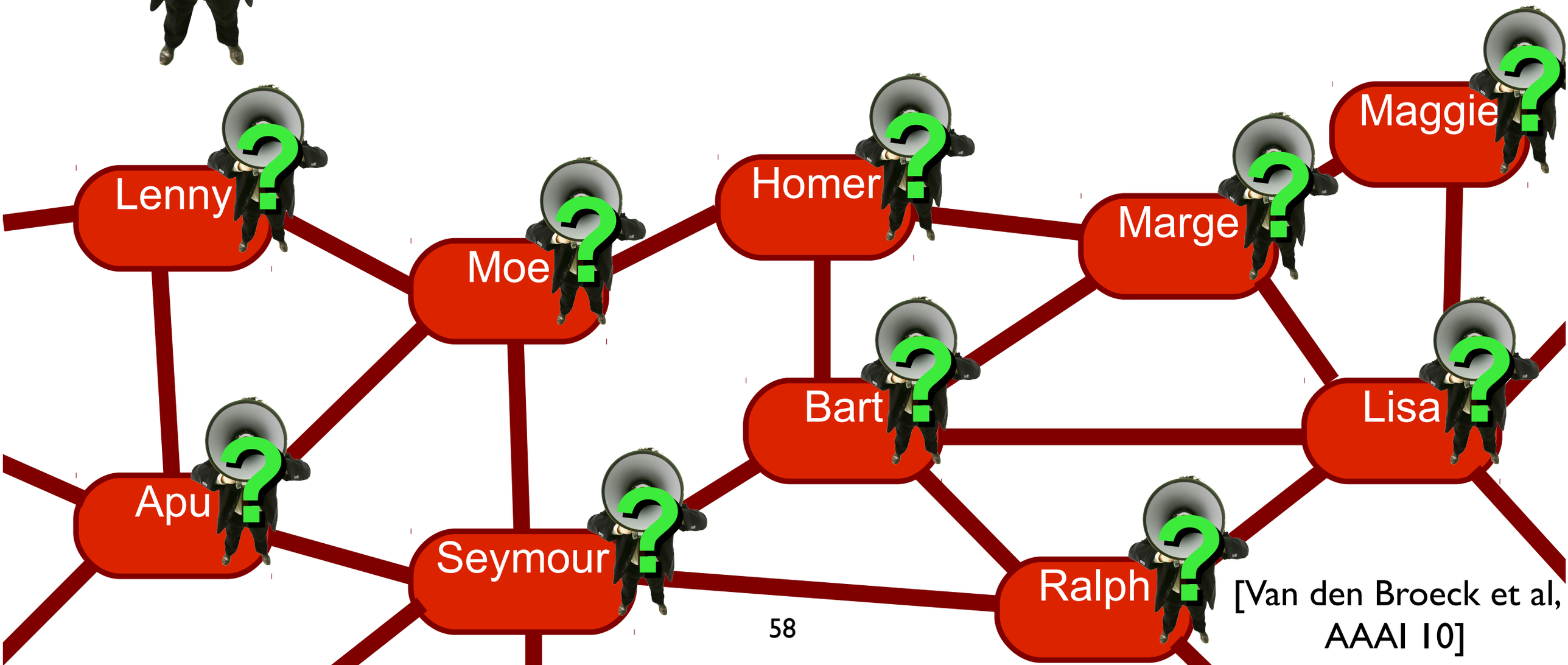
- Modeling (ProbLog and Church, another representative of PP)
- Inference
- **Learning**
- **Dynamics and Decisions**

... with some detours on the way

Viral Marketing



Which advertising **decide** truth values of strategy maximizes some atoms expected profit?



[Van den Broeck et al, AAAI 10]

DTProbLog

```
? :: marketed(P) :- person(P).

0.3 :: buy_trust(X,Y) :- friend(X,Y).
0.2 :: buy_marketing(P) :- person(P).

buys(X) :- friend(X,Y), buys(Y), buy_trust(X,Y).
buys(X) :- marketed(X), buy_marketing(X).
```

decision fact: true or false?

```
buys(P) => 5 :- person(P).
marketed(P) => -3 :- person(P).
```

utility facts: cost/reward if true

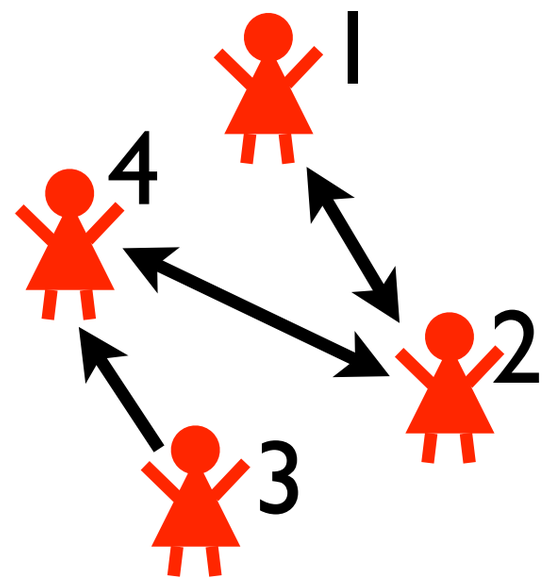
probabilistic facts + logical rules

probability = 0.0032

```
marketed(1)        marketed(3)
   bt(2,1)   bt(2,4)        bm(1)
buys(1)    buys(2)
```

task: find strategy that maximizes expected utility

solution: using ProbLog technology

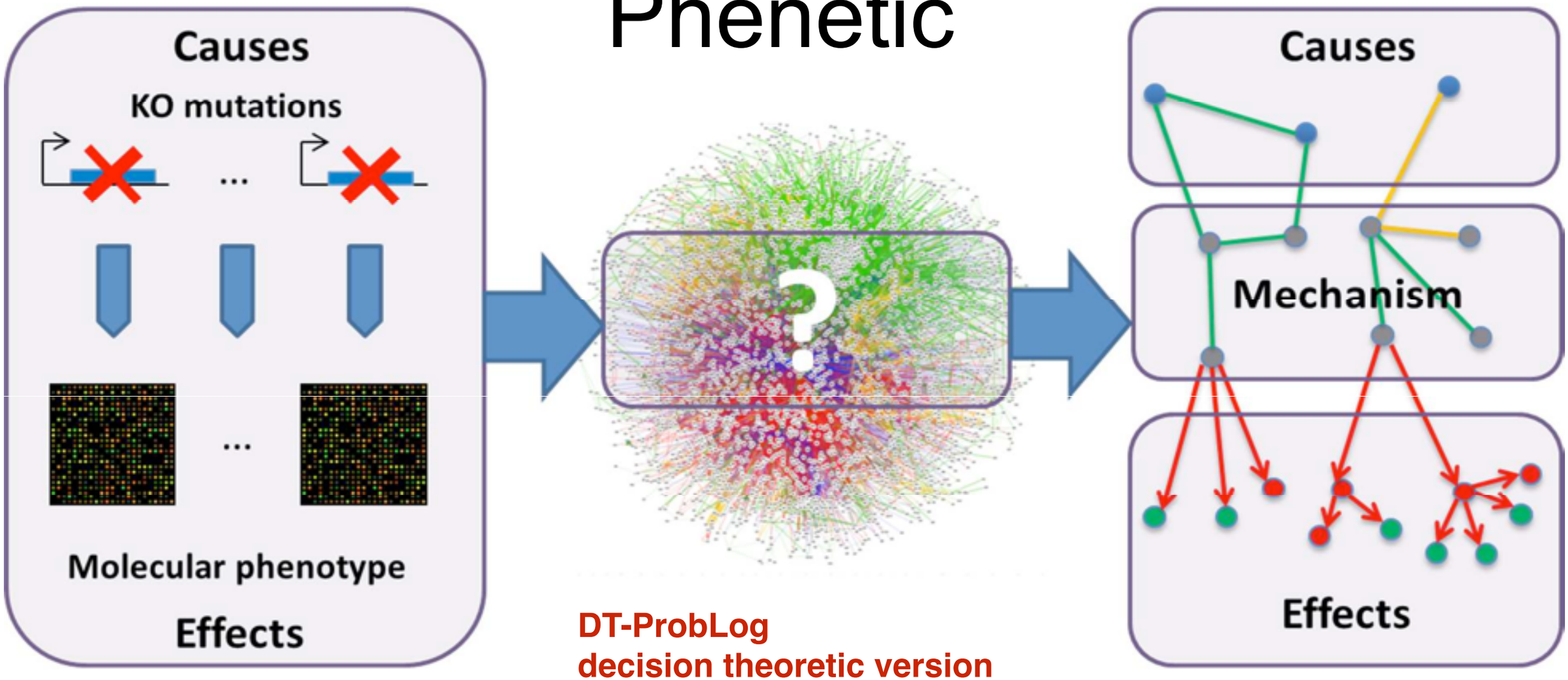



```
person(1).
person(2).
person(3).
person(4).

friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

world contributes 0.0032×4 to expected utility of strategy

Phenetic



DT-ProbLog
decision theoretic version

- Causes: Mutations
  - All related to similar phenotype
- Effects: Differentially expressed genes
- 27 000 cause effect pairs

- Interaction network:
  - 3063 nodes
    - Genes
    - Proteins
  - 16794 edges
    - Molecular interactions
    - Uncertain

- Goal: connect causes to effects through common subnetwork
  - = Find mechanism
- Techniques:
  - DTProbLog [Van den Broeck]
  - Approximate inference

Can we find the mechanism connecting causes to effects?

[De Maeyer et al., Molecular Biosystems 13, NAR 15]

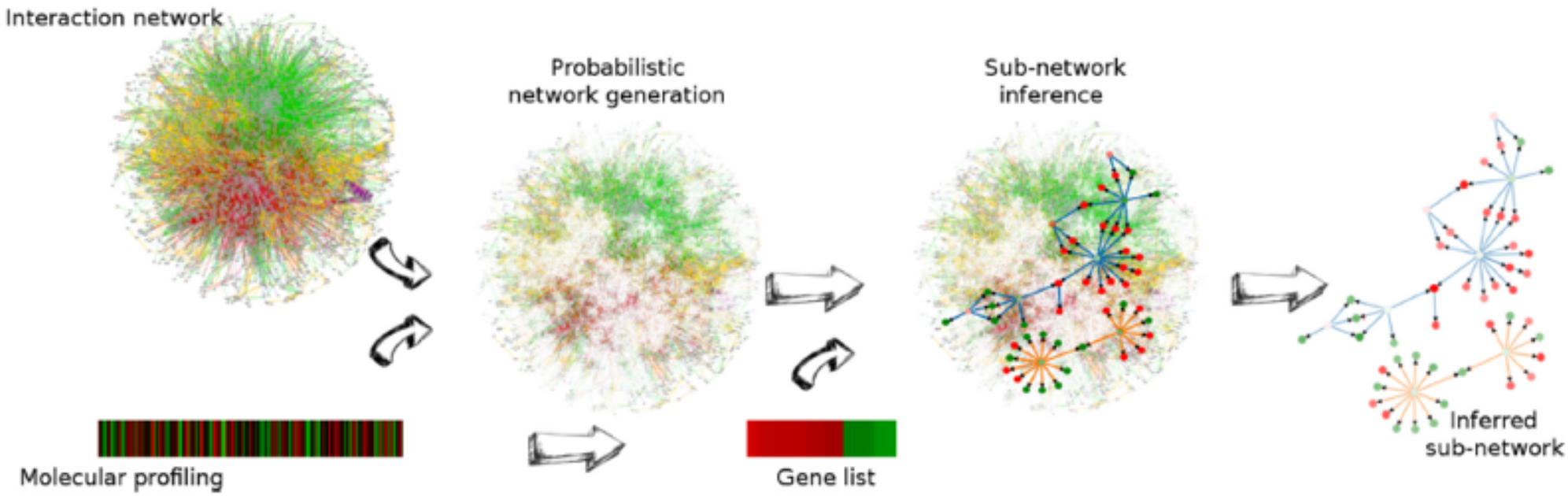


Figure 1. Overview of PheNetic, a web service for network-based interpretation of 'omics' data. The web service uses as input a genome wide interaction network for the organism of interest, a user generated molecular profiling data set and a gene list derived from these data. Interaction networks for a wide variety of organisms are readily available from the web server. Using the uploaded user-generated molecular data the interaction network is converted into a probabilistic network: edges receive a probability proportional to the levels measured for the terminal nodes in the molecular profiling data set. This probabilistic interaction network is used to infer the sub-network that best links the genes from the gene list. The inferred sub-network provides a trade-off between linking as many genes as possible from the gene list and selecting the least number of edges.

[De Mayer et al., NAR 15]

A true application

A tool for Computational Biology

Based on decision theoretic variation of ProbLog

ProbLog / Prob. Programming for prototyping

More specialised inference engine was needed

also some special purpose approximations

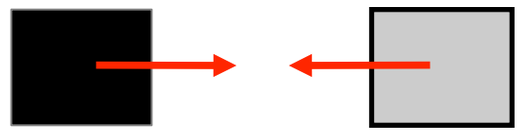
Distributional Clauses (DC)

- A probabilistic logic language
- Logic (relational): a template to define random variables
- MDP representation in Dynamic DC:
  - Transition model: $Head_{t+1} \sim Distribution \leftarrow Conditions_t$
  - Applicable actions: $applicable(Action)_t \leftarrow Conditions_t$
  - Reward: $reward(R)_t \leftarrow Conditions_t$
  - Terminal state: $stop_t \leftarrow Conditions_t$
- The state can contain:
  - Discrete, continuous variables
  - The number of variables in the state can change over time

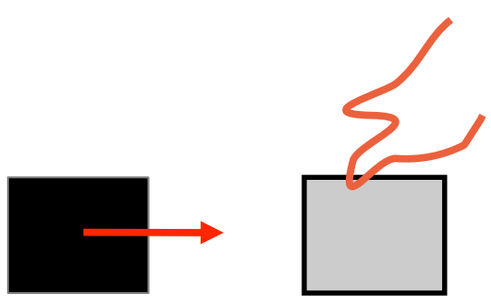
Magnetic scenario

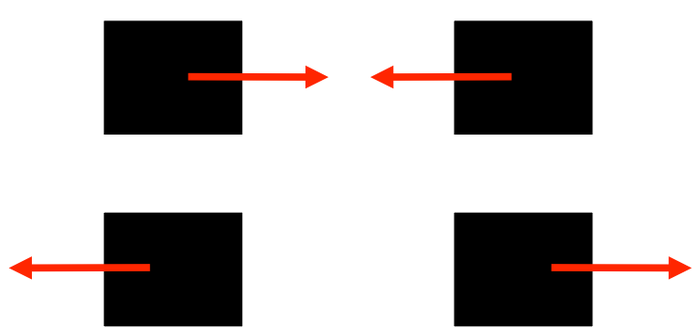
- 3 object types: magnetic, ferromagnetic, nonmagnetic

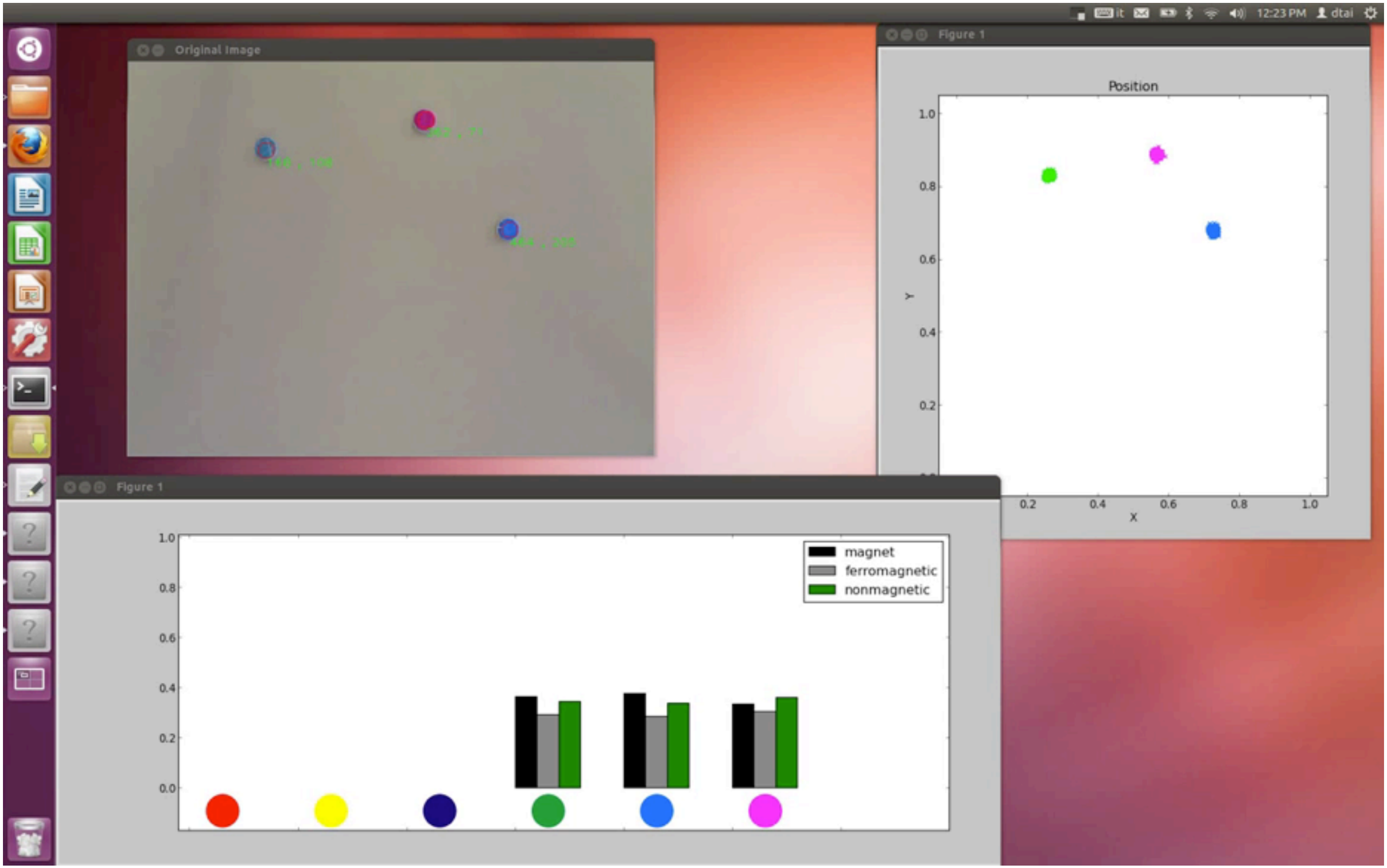
- Nonmagnetic objects do not interact
- A magnet and a ferromagnetic object attract each other



- Magnetic force that depends on the distance
- If an object is held magnetic force is compensated.






it
12:23 PM
dtai
Original Image
462 , 71
160 , 108
464 , 205
Figure 1
Position
1.0
0.8
0.6
0.4
0.2
Y
0.2
0.4
0.6
0.8
1.0
X
Figure 1
1.0
0.8
0.6
0.4
0.2
0.0
magnet
ferromagnetic
nonmagnetic

Magnetic scenario

- 3 object types: magnetic, ferromagnetic, nonmagnetic

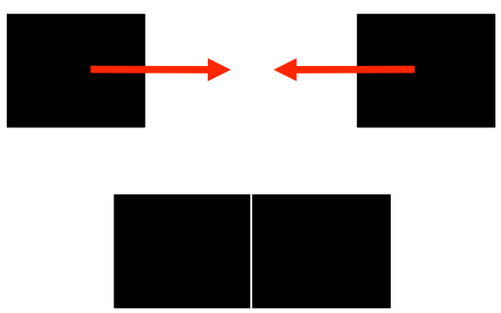
$$\text{type}(X)_t \sim \text{finite}([1/3\text{:magnet}, 1/3\text{:ferromagnetic}, 1/3\text{:nonmagnetic}]) \leftarrow \text{object}(X).$$

- 2 magnets attract or repulse

$$\text{interaction}(A,B)_t \sim \text{finite}([0.5\text{:attraction}, 0.5\text{:repulsion}]) \leftarrow \text{object}(A), \text{object}(B), A<B, \text{type}(A)_t = \text{magnet}, \text{type}(B)_t = \text{magnet}.$$

- Next position after attraction

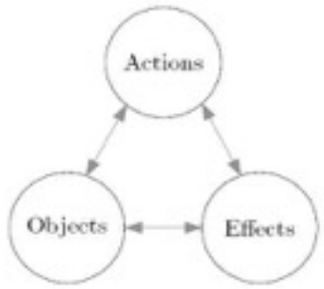
$$\text{pos}(A)_{t+1} \sim \text{gaussian}(\text{middlepoint}(A,B)_t, \text{Cov}) \leftarrow \text{near}(A,B)_t, \text{not}(\text{held}(A)), \text{not}(\text{held}(B)), \text{interaction}(A,B)_t = \text{attr}, c/\text{dist}(A,B)_t^2 > \text{friction}(A)_t.$$



$$\text{pos}(A)_{t+1} \sim \text{gaussian}(\text{pos}(A)_t, \text{Cov}) \leftarrow \text{not}(\text{attraction}(A,B)).$$

Learning relational affordances

Learn probabilistic model



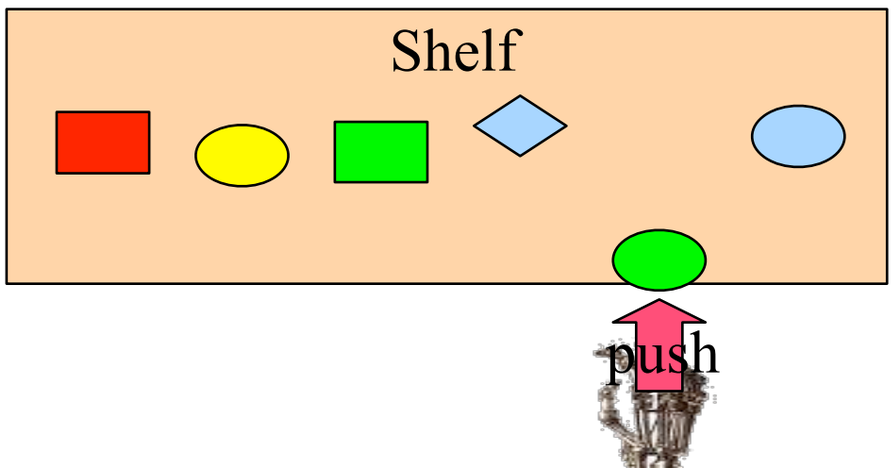
Inputs	Outputs	Function
(O, A)	E	Effect prediction
(O, E)	A	Action recognition/planning
(A, E)	O	Object recognition/selection

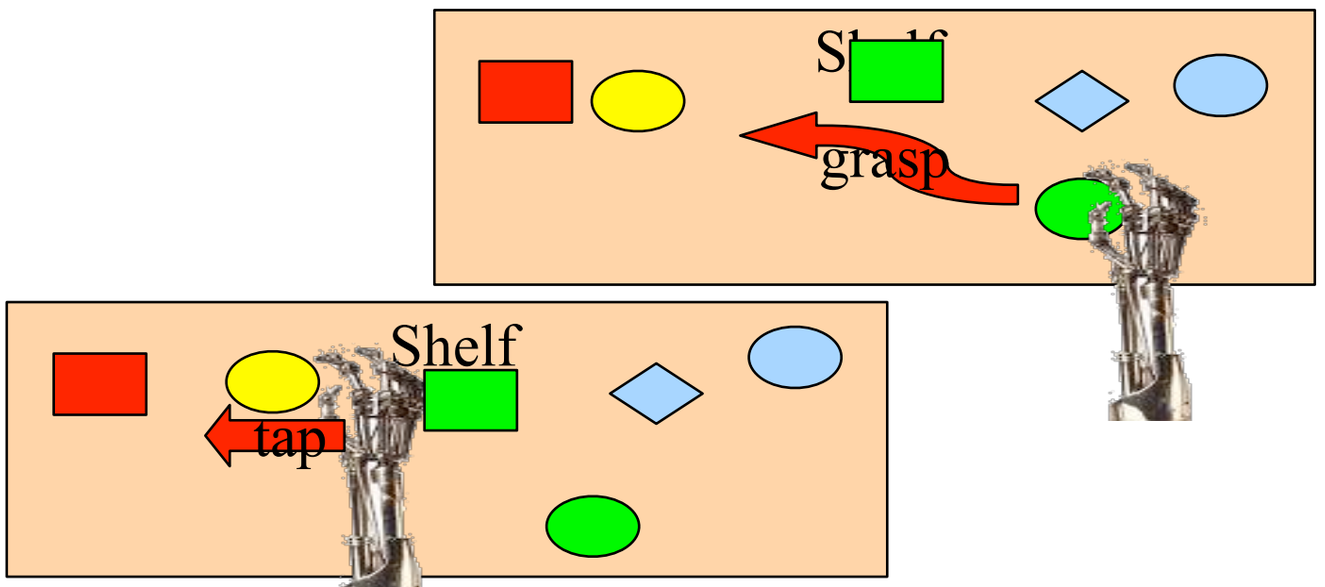
Learning relational affordances between two objects (learnt by experience)

From two object interactions

Generalize to N

***Moldovan** et al. ICRA 12, 13, 14, PhD 15*



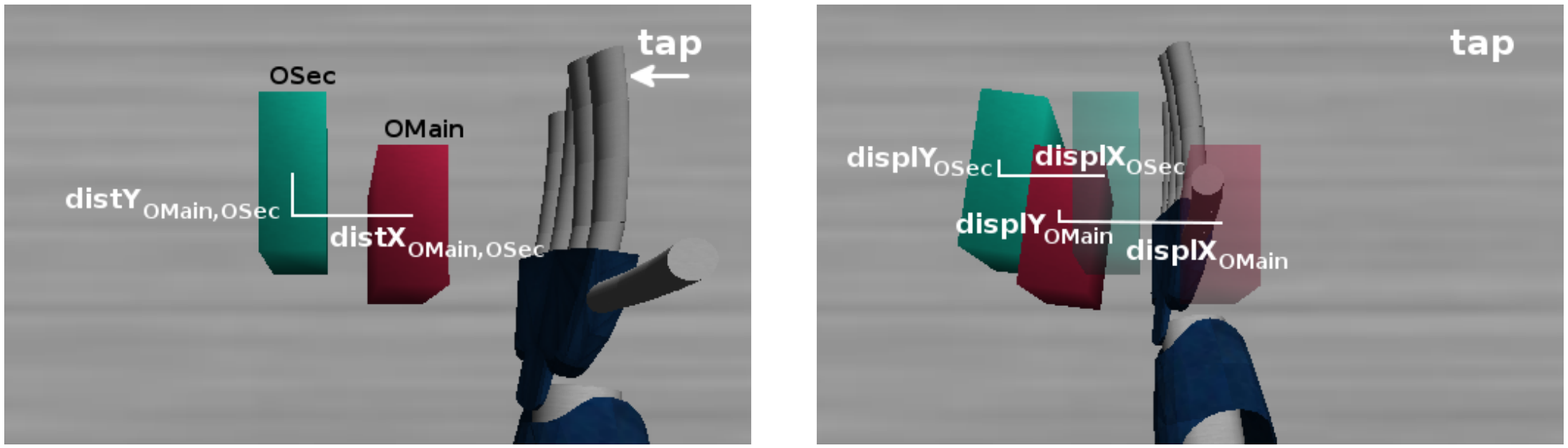


Learning relational affordances between two objects (learnt by experience)

Right Arm

Examples

What is an affordance ?



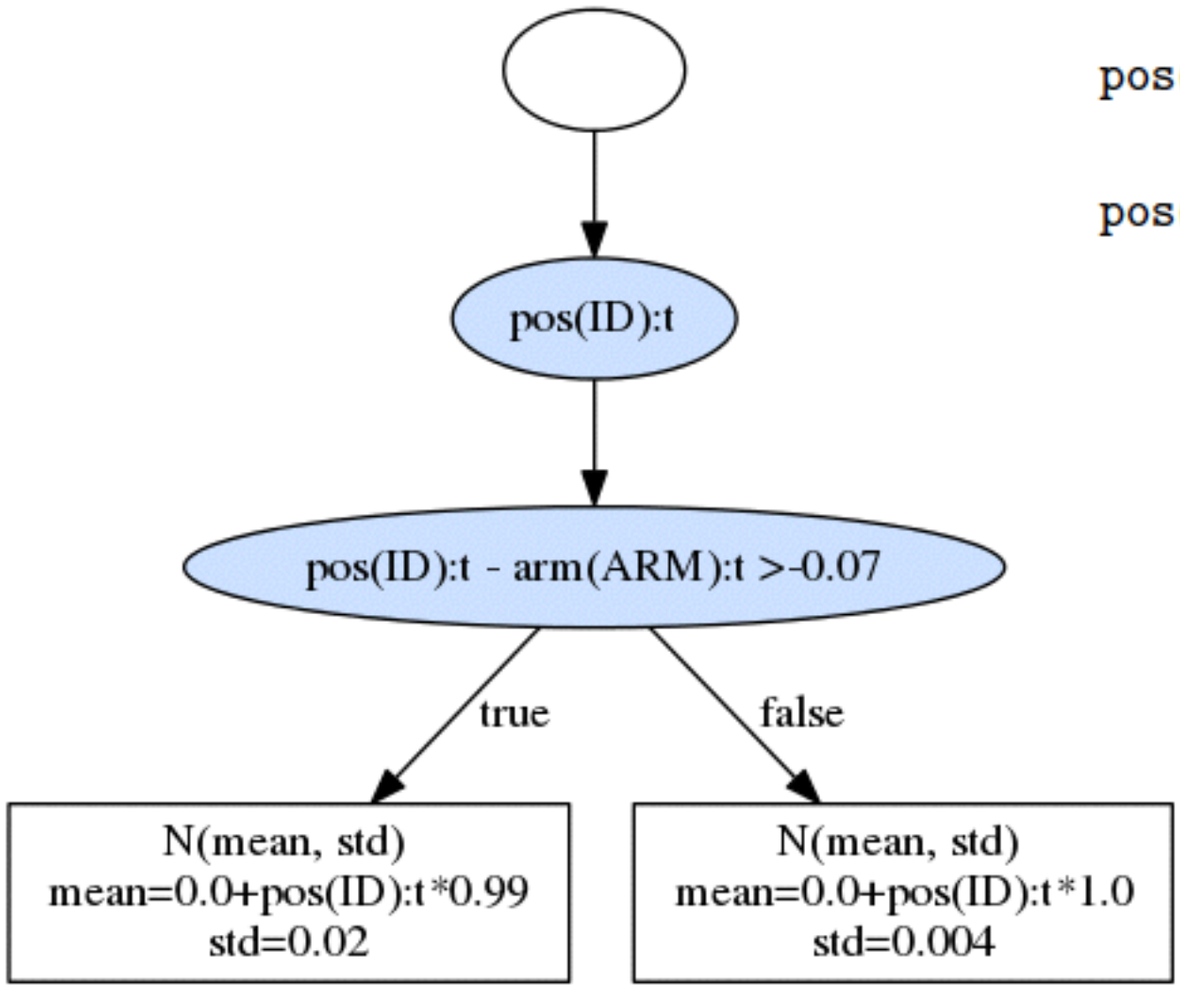
Clip 8: Relational O before (l), and E after the action execution (r).

Table 1: Example collected O, A, E data for action in Figure 8

Object Properties	**Action**	**Effects**
$shape_{O_{Main}} : sprism$ $shape_{O_{Sec}} : sprism$ $distX_{O_{Main},O_{Sec}} : 6.94cm$ $distY_{O_{Main},O_{Sec}} : 1.90cm$	$tap(10)$	$displX_{O_{Main}} : 10.33cm$ $displY_{O_{Main}} : -0.68cm$ $displX_{O_{Sec}} : 7.43cm$ $displY_{O_{Sec}} : -1.31cm$

- Formalism — related to STRIPS but models delta
- but also joint probability model over A, E, O

Learning the model
Key ideas



$$\texttt{pos(ID)}_{t+1} \sim \texttt{gaussian}(0.99 * \simeq\texttt{pos(ID)}_t, .02) \leftarrow \simeq\texttt{pos(ID)}_t - \simeq\texttt{arm(ARM)}_t > -0.07.$$

$$\texttt{pos(ID)}_{t+1} \sim \texttt{gaussian}(\simeq(\texttt{pos(ID)}_t), .004) \leftarrow \simeq\texttt{pos(ID)}_t - \simeq\texttt{arm(ARM)}_t <= -0.07.$$

1. Learn a regression tree
2. Map it onto DCs
   (satisfies disjointness requirement)
3. Use complex “aggregate” features
4. Use pseudo-likelihood to score

Some non branching nodes …

Learning the model
Key ideas

Distributions. We envisage the following types of distributions $\mathcal{D}(f_c(\mathbf{s}_t))$ in Eq. 5:

- a **linear Gaussian distribution** defining $\mathcal{D}(f_c(\mathbf{s}_t)) = N(\mu, \sigma)$ where $\mu = \alpha + \sum_{f \in f_c(\mathbf{s}_t)} f_c \cdot \beta_{f_c}$ if Q_{t+1}'s range is continuous
- a **softmax** or normalized exponential model defining $\mathcal{D}(f_c(\mathbf{s}_t))$ as a $\texttt{softmax}(\beta^T f_c(\mathbf{s}_t))$ if Q_{t+1} ranges over discrete values, where the β_j are vectors of weights for the vector of features $f_c(\mathbf{s}_t)$ and value v_j in Q_{t+1}'s range.

$$\texttt{agg}\{(U_1 \text{ op } \texttt{U}_2), \texttt{C})\}$$

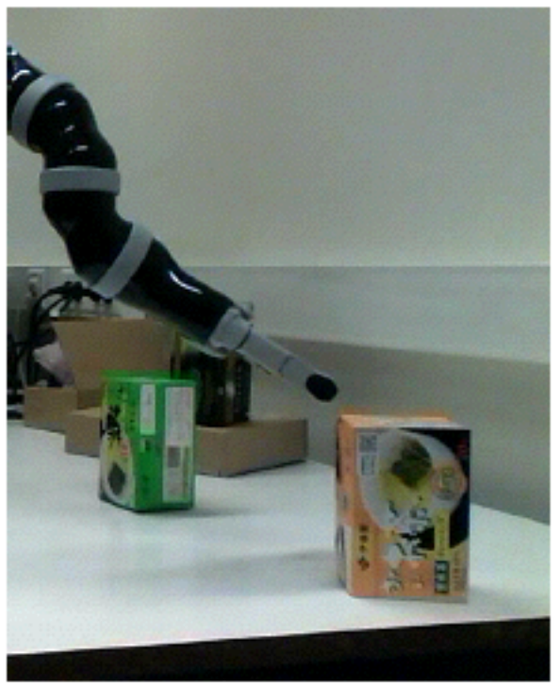
$$\texttt{min}\{(pos_x(\texttt{O}_1)_t - pos_x(\texttt{O}_2))_t, \texttt{O}_1 \neq \texttt{O}_2\}$$

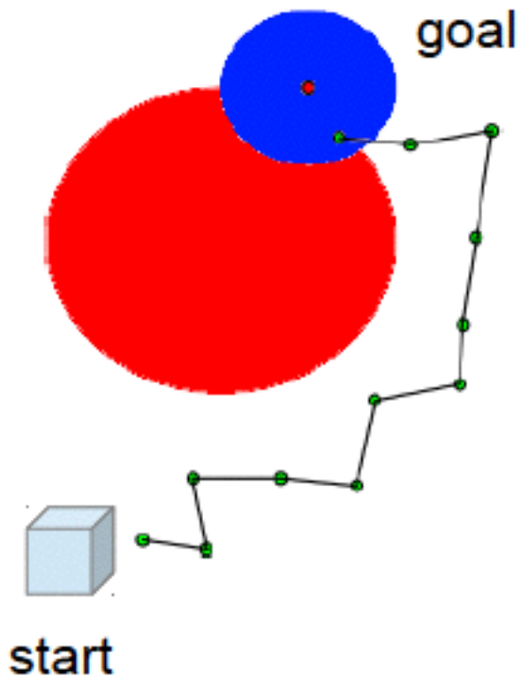
$$score(DC, e) = \sum_{(h \sim \mathcal{D} \leftarrow body) \in DC} \sum_{\theta : body\theta \subseteq I_e} p_{\mathcal{D}}(I(h\theta) | I(body\theta))$$

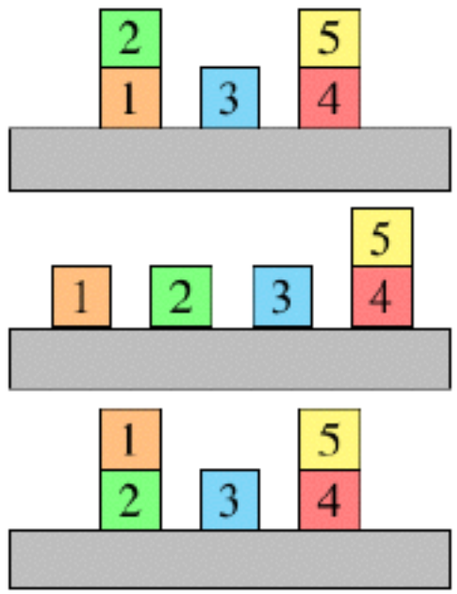
Planning

- Main task: probabilistic planning

  Find the best action to achieve the goal
- Discrete + continuous + relational representation





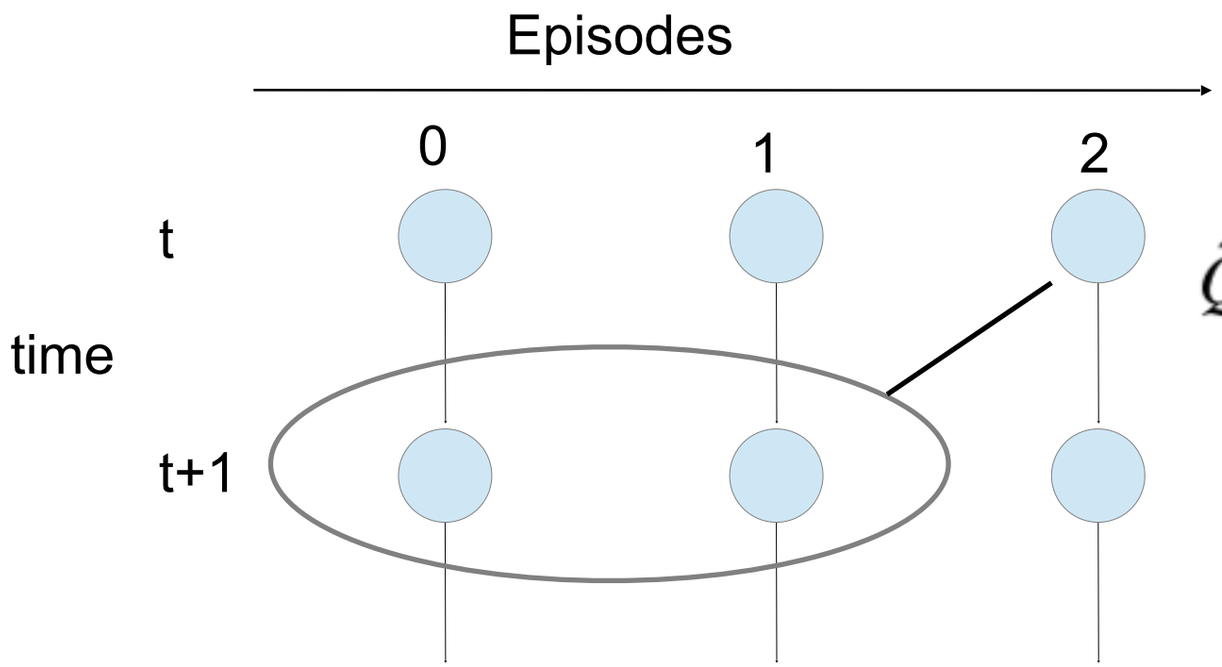


[Nitti et al ECML 15]

How?

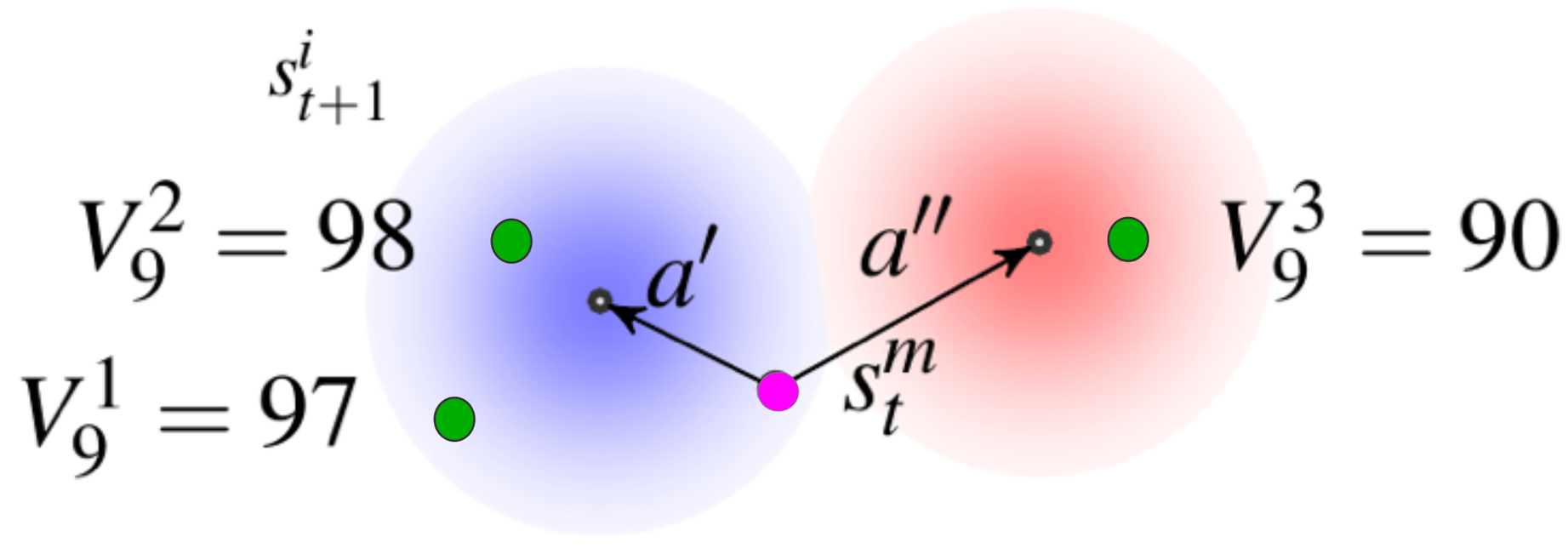
- Hybrid relational MDP
- Monte-Carlo (sampling)
- Exploit the model
  (sample-based planners do not exploit the MDP model when available)
- Non-parametric (lazy learning)
- Abstract sampled episodes (not states)

HYPE: Q-function evaluation



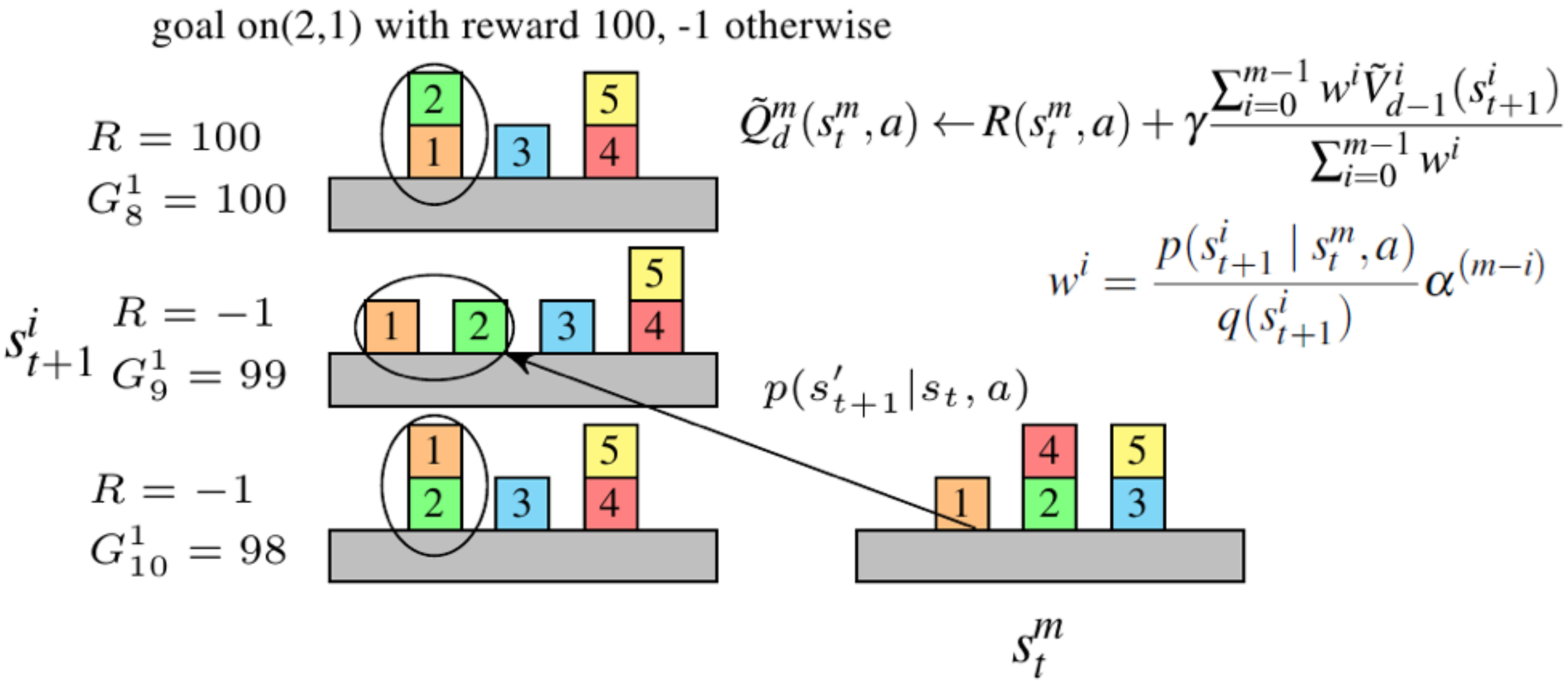
$$\tilde{Q}_d^m(s_t^m, a) \leftarrow R(s_t^m, a) + \gamma \frac{\sum_{i=0}^{m-1} w^i \tilde{V}_{d-1}^i(s_{t+1}^i)}{\sum_{i=0}^{m-1} w^i}$$

$$w^i = \frac{p(s_{t+1}^i \mid s_t^m, a)}{q(s_{t+1}^i)} \alpha^{(m-i)}$$

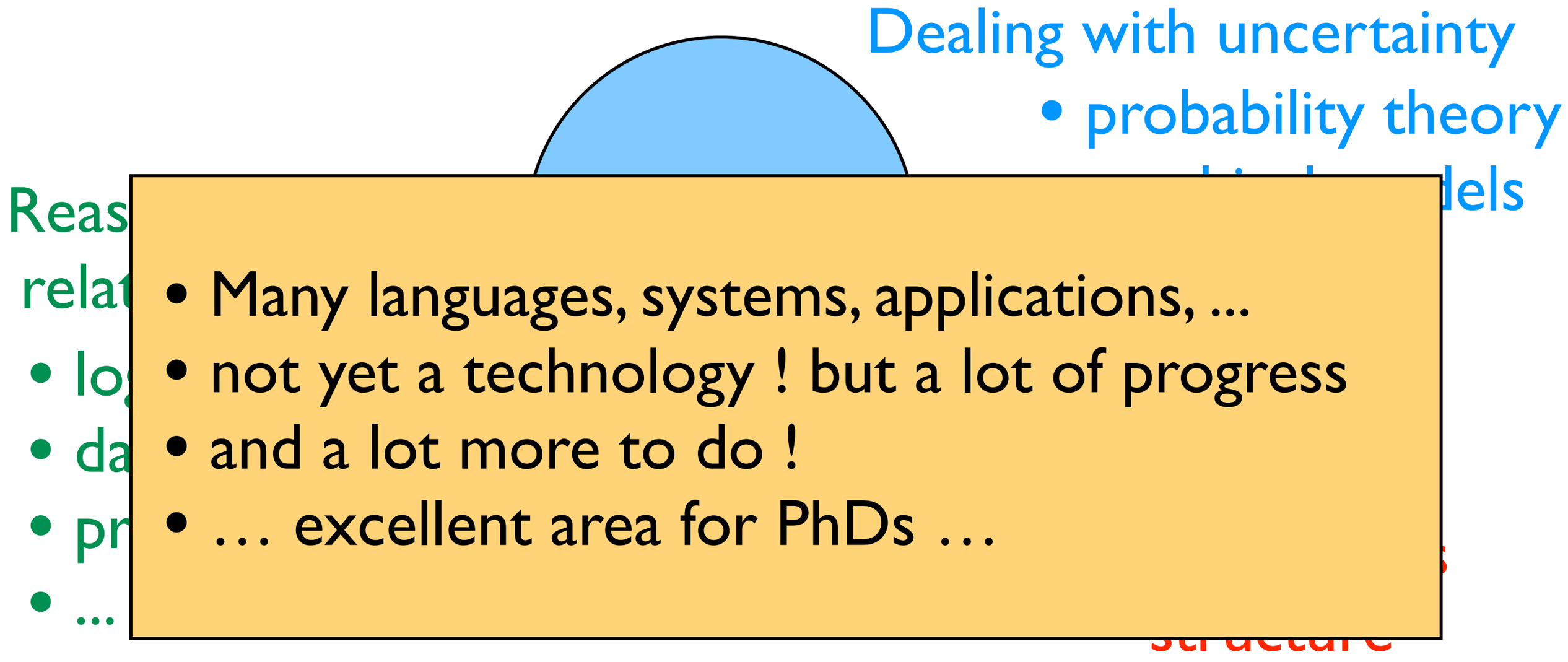


Partial interpretations

- Remove irrelevant facts for $\sum R(s_t,a_t)$
- $p(s_{t+1}|s_t,a_t)$ is applied to partial states



A key question in AI:



Statistical relational learning
Probabilistic programming, ...

Maurice Bruynooghe
Bart Demoen
Anton Dries
Daan Fierens
Jason Filippou
Bernd Gutmann
Manfred Jaeger
Gerda Janssens
Kristian Kersting
Angelika Kimmig
Theofrastos Mantadelis
Wannes Meert
Bogdan Moldovan
Siegfried Nijssen
Davide Nitti
Joris Renkens
Kate Revoredo
Ricardo Rocha
Vitor Santos Costa
Dimitar Shterionov
Ingo Thon
Hannu Toivonen
Guy Van den Broeck
Mathias Verbeke
Jonas Vlasselaer

Thanks !

http://dtai.cs.kuleuven.be/problog